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ASSESSING POTENTIAL ENVIRONMENTAL IMPACTS ACCORDING TO PROBABLE PATTERNS OF SWITCHGRASS ADOPTION IN THE SOUTHEASTERN US

Benjamin Sharp
Clemson University, benjami@clemson.edu

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Benjamin E. Sharp
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Dr. Shelie Miller, Research Advisor
Dr. Cindy Lee, Committee Chair
Dr. Catherine Mobley
Dr. Stephen Moysey
Dr. Leidy Klotz

ABSTRACT

To assess the overall net impact of an emerging technology, life cycle assessment (LCA) must be accompanied by projections of adoption. Diffusion of innovation research provides tools that incorporate economic and social variables to explain and forecast integration of technologies. A switchgrass-to-ethanol case study for the southeastern U.S. is used to demonstrate methods for gauging aggregate environmental effects of an emerging energy technology. Before applying diffusion concepts, breakeven capacities are calculated for land in row crops, hay, pasture and marginal land. Breakeven curves are generated to provide upper bounds to switchgrass adoption over a range of farm-gate prices. The amount and type of land converted to switchgrass provides estimates for the total land use change effects as well as for biomass production and overall impact of the regional switchgrass-to-ethanol system, which is measured by greenhouse gas (GHG) emissions, net fossil energy, and nitrate loss. Maximum switchgrass adoption is assessed within breakeven areas for prices of $50, $100, and $150 per metric ton (Mg). Regression analysis shows that hectares of pasture and hay lands are historically not correlated with crop production profit, which suggests minimal switchgrass adoption. Land in active row crops and marginal land have historically converted land in relation to profitability of crops; consequently, switchgrass is expected to be planted on 75% of active cropland and marginal land for which it breaks even. Next, the Bass diffusion model is used to approximate the rate of adoption using previous applications of agricultural adoption. Finally, previous studies of life cycle impacts for the system are aggregated according to adoption

estimates at each price. At \$100 Mg^{-1}, switchgrass is projected to be grown on about 0.8 million hectares of land in row crops and 0.5 million hectares of the other land categories. This area of production translates to 5.4 billion liters of ethanol, which is about 9% of the gasoline consumed annually in the region. Because land use change (LUC) benefits are enhanced by primarily converting row crops to switchgrass, annual carbon dioxide equivalents of GHG emissions are reduced by about 2 billion kg CO_2e yr^{-1}. About 20 years are required to reach such a production level even though national mandates are set for 2022. Including projections of behavior in environmental assessments can inform proactive policy measures that optimize effects of emerging energy technologies.

DEDICATION

“Which is the “true” or “valid” experience? ...

One must look both *along* and at everything.”

– C.S. Lewis, *Meditation in a Toolshed*

The selfish process of formal education can only be justified by paying it forward and through proper recognition of efforts from those who make it possible. I am indebted to many friends and family but foremost Jules.

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Jose Alfaro had a hand in this effort, and Jim Chamberlain deserves credit for blazing a trail. These two gentlemen exemplify how returning to the vulnerable position of a student is only a formal expression of what we must be every day. (James 2:14-26)

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1 INTRODUCTION

1.1 Research Synopsis

The goal of this research is to further extend environmental assessments to include more details regarding the effects of human behavior on emerging systems. A meaningful evaluation of a new technology must account for impacts throughout the stages of the life cycle as well as the social and economic influences that shape the technology's integration into existing regimes. By quantifying the expected role of behavior, life cycle assessment (LCA) results can be appropriately aggregated and provide context for potential environmental outcomes at different points during the integration process. Such analysis incorporates the social, economic, and environmental aspects of sustainability, which offers greater insight toward proactive public policy regarding prospective energy systems. An assessment of sustainability for an emerging technology not only depends on LCA estimates, but also on who adopts the technology, what is displaced, and the rate and extent of diffusion.

To develop the analysis, a case study for a prospective switchgrass-to-ethanol industry for the southeastern U.S. is examined. Diffusion of innovation analysis tools are considered to assess the degree to which farmers may adopt switchgrass. The capacity for switchgrass production is framed by the potential to increase profit on different types land at different farm-gate prices. Estimates of the amount of lands that are converted to switchgrass over time allows for land use change effects along with LCA of ethanol conversion to be translated into aggregate impacts for the region. The assessment illustrates the potential for a switchgrass-to-ethanol system to displace gasoline in context with corresponding environmental consequences and biofuel policy timetables.

1.2 Background and Objectives

U.S. policy has supported the continued expansion of biofuels through conversion of switchgrass into ethanol, which implies that many southeastern farmers will be faced with the choice of growing a new bioenergy crop. The case study merits analysis that includes characterizing the potential of farmers to grow switchgrass because farmer behavior largely determine the size and overall impact of the regional switchgrass-to-ethanol system.

There are few studies that have combined detailed analysis of new innovation diffusion with LCA studies; consequently, possible methods are explored that combine diffusion of innovation with LCA. The combination of analyses is an original approach for assessing sustainability of emerging systems.

The three objectives to this research are:

(1) A critical review of relevant literature from life cycle assessment and diffusion of innovation research provides a backdrop for bridging the gap between adoption of a new technology and assessing environmental consequences. Diffusion of innovation research provides tools that incorporate economic and social variables to explain and forecast integration of technologies. Identifying and quantifying causal relationships from diffusion analysis provides context and suggests practical scenarios for aggregating LCA results of a new innovation.

(2) Before applying diffusion of innovation concepts, the economic feasibility of switchgrass production for the region is evaluated. With no significant market for switchgrass, the prospective price is a key unknown for the future of the industry. Using switchgrass farm-gate price as an independent variable, the potential for four different types of land to profit with switchgrass is approximated.

(3) Tools explored in the first objective and breakeven capacities found in the second objective are used to assess prospective switchgrass adoption in the region. Estimates for the maximum level of adoption are combined with previous LCA studies of respective impacts from converting different types of land to switchgrass. The total yearly contribution of greenhouse gas emissions, net fossil energy consumption, and the amount of nitrogen entering natural waters are measured for the switchgrass-to-ethanol system for the region. Switchgrass production scenarios over time also provide estimates of total annual ethanol generation, which inform progress toward displacement of gasoline and achieving biofuel targets set by national policy.

The above objectives are addressed in Chapters 2 – 4. Chapter 5 summarizes the research methods and results.

2 APPLYING DIFFUSION OF INNOVATION METHODS TO LIFE CYCLE ASSESSMENTS OF EMERGING TECHNOLOGY

A review of diffusion of innovation research in conjunction with life cycle assessment methods gives a background for selecting appropriate methods to apply to prospective switchgrass adoption in the region. The overall environmental impact of new technology not only depends on the degree of market penetration, but is also characterized by what is displaced in the process. Furthermore, adopter utilization of emerging systems is variable and must also be taken into account. In this case, the type of land that is converted to switchgrass influences land use change effects as well as yield potential.

Diffusion of innovation research is an established field of marketing and management science. The purpose is to describe and forecast probable patterns of adoption in order to provide management and advertising strategies. This research uses a novel combination of adoption analysis along with environmental assessment of innovation. Results are useful for crafting public policies that promote sustainability in relation to new environmentally-oriented technology.. For the switchgrass-to-ethanol case study, the adoption of switchgrass by farmers in the southeast is analyzed in terms of the different types of land they operate.

The remainder of the chapter is a journal article that explores methods for analyzing diffusion of potentially any new technologies in terms of environmental impacts. It is intended for submission to *Environmental Science & Technology* as a critical review.

2.1 Abstract

To gauge the overall net impact of an emerging technology, life cycle assessment (LCA) must be accompanied by projections of adoption. Diffusion of innovation research provides tools that incorporate economic and social variables to explain and forecast integration of technologies. Identifying and quantifying cause-effect relationships from diffusion analysis provides context and suggests consequences that shape LCA of a new innovation. This information can be used to estimate the extent of environmental impacts through projections of market penetration and can illustrate how formative events may lead to different environmental outcomes. The two primary perspectives in diffusion research are aggregate models that use an overarching equation to describe adoption, and micro-level models that use a bottom-up approach of simulating adoption behavior of individuals. An overview of each perspective explores motivations and mechanisms that drive adoption in order to inform scenarios for consequential life cycle assessments of emerging technologies. Findings suggest pathways to consider LCA as part of proactive rather than reactive environmental policy.

2.2 Introduction

Researchers have used life cycle assessment (LCA) to measure expected environmental effects of a prospective technology on a functional unit basis; however, in order to project the total impact of a technology LCA must be coupled with additional methods that estimate the extent that the technology is adopted. A LCA may indicate that a new innovation is environmentally superior, but its ability to reduce harmful effects for a region depends on the level of adoption. This work explores diffusion of innovation research for concepts that can accompany LCA as a means to estimate the overall net environmental impact of emerging technologies.

Aggregate environmental outcomes that are attributed to a new innovation entering a market are determined by LCA measures and market penetration. First, the total impact depends on the net life cycle impacts compared to prevailing technologies. Second, total impact depends on the degree the innovation is integrated into the defined socio-technological system according to the corresponding displacement of existing technologies within the system. Diffusion of innovation research analyzes the process by which new services or products penetrate a market according to various social influences (Peres et al., 2010). The combination of projected LCA and diffusion of innovation results can provide a comprehensive and practical assessment of the overall change in environmental impact of a future system. The basic methods of innovation diffusion as well as their potential integration with LCA are investigated.

Due to the magnitude and uncertainty surrounding many emerging technological developments, there remains an analytical gap for including more in-depth analysis of social and economic forces in conjunction with environmental assessment (Guinée et al., 2011). A review innovation diffusion literature reveals approaches for acquiring data and utilizing appropriate methods to forecast the effect that human behavior has on the extent of environmental outcomes from new innovations.

Performing comprehensive evaluations of emerging technology before they are established may expose potential unintended environmental consequences

(Miller et al., 2012). The dynamics of major innovations diffusing within a region can initiate important changes environmentally and behaviorally as existing products and practices are displaced. For example, the unprecedented expansion of mobile phone use into different areas around the world has brought environmental consequences as well as social and economic effects (Fehske et al., 2011; Peres et al., 2010). Anticipating such progressions allows for early establishment of proactive measures to manage the end-of-life effects of hundreds of millions of phones (Yu et al., 2010).

The diversity and complexity of socio-technological systems suggest a wide range of potential approaches for projecting adoption patterns (Berkhout et al., 2004). To frame possible techniques, developments in LCA that support projections of aggregate environment impact are summarized. Background on diffusion of innovation research then provides a foundation for examining different methods from an environmental assessment point of view. Methodologies are explored in terms of two forecasting categories. The first method is a top-down approach or macro-level model. The second approach is a bottom-up perspective or modeling at the micro-level. The appropriate combination of techniques along with scenario development are discussed according to available data and assumptions applied to a particular system.

2.3 Contributions from LCA

Over the last couple of decades, LCA has gained popularity for use in environmental management decisions (Guinée et al., 2011). LCA estimates the degree of impact at various stages of a product or service. Gathering and interpreting life cycle inventory data through the supply chain, use phase, and end-of-life phase allow for better process management to reduce ecological damage. The implementation of LCA in policy and business decisions has proven to be an important assessment tool for wide range of technologies and processes (Hertwich, 2005).

During its evolution and standardization, LCA has benefited from developments such as improved databases and more robust methods. The concept of measuring impacts according to a functional unit establishes a foundation for broader analysis and comparison of alternatives with different physical characteristics that carry out similar functions (Frijia et al., 2012; Rebitzer et al., 2004; Udo de Haes and Heijungs, 2007). Life cycle assessment is expected to become increasingly comprehensive in terms of assessing social and economic factors of a system (Guinée et al., 2011). As part of this transition, consequential life cycle assessment has gained greater consideration by accommodating impact measures according to prospective changes to the system that can include behavioral influences (Earles and Halog, 2011; Zamagni et al., 2012; Guinée et al., 2011; Finnveden et al., 2009).

Consequential life cycle assessment (CLCA) differs from conventional or attributional LCA by considering expansion of boundaries and input data for the system (Ekvall and Weidema, 2004). Zamagni et al. (2012) review various CLCA interpretations and propose that CLCA essentially incorporates a market component as part of the analysis. A novel way to use CLCA is to integrate diffusion of innovation analysis. Applying adoption evaluations to CLCA lend themselves to scenario modeling as socio-technological regimes may encounter policy, market, or technological changes that greatly affect results (Höjer et al., 2008; Mathiesen et al., 2009; Zamagni et al., 2012).

For example, prospective development of fuel cell buses was used to illustrate methods for managing consequences and cause-effect relationships for estimating potential global greenhouse gas impact (Sandén and Karlström, 2007). Even though fuel cell for transport has an extremely limited market penetration, investigators were interested in estimating possible long-term reductions in CO_2 emissions due to wider adoption of solid polymer fuel cell (SPFC) buses (Sandén and Karlström, 2007). The study quantified positive and negative feedback for a SPFC system in terms of technology development, market constraints, projections of emissions of existing technologies, and long-term adoption. The primary methods to gauge these affects were through experience curves and scenario models (Sandén and Karlström, 2007). Although the fuel cell buses case study shows potential for significant reductions in CO_2 emissions, outcomes are strongly dependent on early decisions and advances that shape long-term trends.

Analyses that include estimates of market penetration such as the case study above can be improved by applying diffusion of innovation concepts. Greater detail in terms of prospective adoption of fuel cell buses can strengthen trend projections and scenarios of market penetration. Improved scenario assessments in turn provide more reliably aggregated environmental impact estimates.

Another tool used in LCA is cost-benefit analysis (CBA) (Ahlroth et al., 2011; Norris, 2001). A cost-benefit analysis provides an economic basis from which to weigh results from LCA for decision making in production processes, drafting policy, or informing market choices (Ahlroth et al., 2011). Experience curves conceptualize CBA for new technologies by projecting the potential reduction of costs. A technology must be an economically feasible option or projected to be feasible before anticipating meaningful levels of market penetration.

This review considers diffusion of innovation approaches to bridge the above efforts in LCA by more effectively quantifying social and economic influences for emerging technologies. Assessing environmental effects as they pertain to a functional unit provides insight specific to the environmental impact of the product, but not the aggregate environmental effects of actual deployment. Additional techniques from CBA and scenario models move CLCA closer to practical assessments of aggregate impacts of a prospective technology; however, employing concepts from diffusion research can refine scenarios used in LCA. Deeper understanding of expected behavior of potential adopters provides valuable information for estimating impacts due to the multiplicative dynamics of innovation diffusion.

2.4 Diffusion of Innovation Background

Quantifying the diffusion process involves assessing prospective human behavior. In some cases, unlikely products and social initiatives rapidly take off (Gladwell, 2006). In others, seemingly ideal innovations fail to diffuse (Delre et al., 2007; Rogers, 1995). Diffusion of innovation analysis is meant to describe and capture interactions inherent in this process, but predictive capabilities of diffusion analysis remains a debated topic (Kiesling et al., 2012; Parker, 1994). Once sufficient data are available to generate dependable predictions, they are often too late for implementing proactive strategies and instead serve as a descriptive assessment of adoption patterns (Mahajan et al., 1990). Despite forecasting challenges, applying diffusion model results can alleviate some guesswork in CLCA scenarios.

Early diffusion of innovation research established structure for more advanced analysis. Data from studies of agricultural technology led to S-curves as a representation of the cumulative adoption over time (Griliches, 1957). Adopter categories, the rate of adoption, and influences that trigger change characterize adoption curves (Figure 2.1) (Rogers, 1995). Figure 2.1 demonstrates general diffusion behavior over time in terms of both cumulative adoption and the rate of adoption; although, specific diffusion applications are subject to influences that may create responses that deviate from the curves shown. Through observation of various examples of diffusion, a variety of models based on statistical distributions have emerged to represent the rate of adoption (Meade and Islam, 2006). Consideration of network dynamics and the spread of information in terms of overarching communications processes and interpersonal relations generated both a macro and micro analytical perspective (Granovetter, 1973).

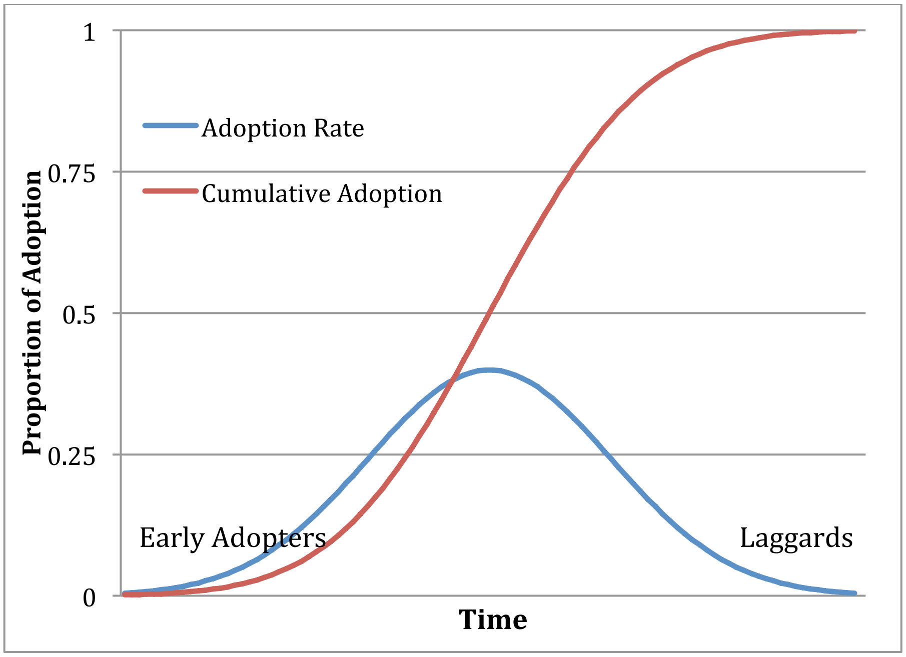


Figure 2.1 Example of Cumulative Adoption S-Curve and Changes in the Rate of Adoption over Time. Adapted from Rogers, E.M., 1995. Diffusion of Innovations. Simon and Schuster, New York, NY 10020.

Diffusion can occur within markets or across market and national boundaries (Meade and Islam, 2006; Peres et al., 2010). Behavior within markets have been studied in terms of takeoffs, cascading generations of technology, software-hardware relationships, network externalities, proximity dependencies, and social network effects (Norton and Bass, 1987; Rogers, 1995; Golder and Tellis, 1997; Baptista, 2000; Peres et al., 2010). For the interest of this review, approaches that model straightforward diffusion of a single technology within a defined market are the main focus.

2.5 Integrating Diffusion of Innovation into LCA

Integrating established diffusion models into estimates of environmental impacts depend on the characteristics of the system and the objectives of analysis. Defining the key environmental impacts associated with a new technology frame the extent of the socio-technological system and the corresponding time period for innovation diffusion analysis. By identifying the objectives of the environmental assessment, key aspects related to diffusion analysis can then be specified. In many cases, environmental regulations and incentives are intertwined in a CLCA (Earles and Halog, 2011). In turn, policies may affect the diffusion process and impose additional time-dependent influences on the system (Geroski, 2000; Rao and Kishore, 2010).

For a given emerging innovation, boundaries defined for the CLCA should be appropriate for the spatial and social structure of potential adopters. The primary piece of information to gain from diffusion of innovation is the total number of units adopted. This projected value translates unit-based LCA estimates into total potential impacts generated by the innovation. For instance, the number of households who adopt solar technology for a defined area determines the number of units of displaced electricity from the grid.

The environmental effects that are linked to the innovation also provide a context in terms of background systems, technological changes, markets, and time horizons and serve as guidelines for defining the boundaries of the CLCA (Ekvall and Weidema, 2004; Weidema et al., 1999). Net CLCA impact results must account for displaced or background systems along with the projected LCA of the emerging technology (Lemoine et al., 2010; Pehnt, 2006). To aggregate the net impacts between background systems and the new technology, the amount displaced and the amount adopted must be approximated. Continuing with the residential solar example, the mix of coal, natural gas, and nuclear power that generate electricity for the region must be calculated to find the net greenhouse gas benefit from the adoption of solar-powered electricity.

In terms of the time frame, complete diffusion of many innovations is about 25 years (Golder and Tellis, 2004). Within the duration of diffusion, some environmental impacts of interest are may strongly depend on time and space. For example, criteria air pollutants or eutrophication effects are associated with cyclical as well as cumulative consumption over a relatively short timetable. Examining dynamics during the diffusion process is especially useful for those cases where the rate and timing of adoption have strong implications for effects with transitory thresholds.

For most cases, the environmental effects during the diffusion of a technology is much less important than the overall cumulative impact and market penetration (Popp et al., 2009). Greenhouse gas emissions, for example, imply an eventual aggregate annual release estimate. On the other hand, policies generally have timelines that are aimed at spurring efforts toward particular goals. There are many examples at the national level for an assortment of energy technologies. In Germany, programs such as the "100,000 Roofs" program for solar cells was realized by 2001 (Jacobsson and Lauber, 2006). In the U.S., a mandate for biofuel production requires 36 billion gallons by 2022 (USDA, 2010). Applying a diffusion-based CLCA to policy is likely to require appropriate accounting of policy influences as well as possible time horizons that may occur at different points on the S-curve.

Returning to the fuel cell buses example, the authors categorize diffusion in terms of positive and negative feedback (Sandén and Karlström, 2007). In the early stages of market penetration, positive feedback mechanisms such as investment and policy support are important for initiating growth in the market (Sandén and Karlström, 2007). Once the technology reaches mature stages, the important feedback influences may largely be negative. For instance, supply chain constraints and market limitations could hamper the extent of cumulative adoption (Sandén and Karlström, 2007). Diffusion of innovation analysis can help interpret the effects of positive feedback mechanisms on ultimate market penetration whereas CLCA analysis can reveal production constraints. Combining LCA with diffusion of innovation methods can refine scenarios with which to estimate the long term effects that fuel cell buses may have on greenhouse gas emissions.

2.6 Approaches for Projecting Diffusion

The cumulative adoption S-curve from Figure 2.1 implies that adopters enter the market at different rates (Bass, 1980). Diffusion of innovation research is largely divided into two viewpoints for describing this behavior (Meade and Islam, 2006; Peres et al., 2010). Researchers consider the population of potential adopters homogeneous or heterogeneous in terms of resources, connectivity, and utility of the innovation (Bass et al., 1994; Chatterjee and Eliashberg, 1990; Gatignon, 2010; Goldenberg et al., 2010; Laciana et al., 2013; Parker, 1994; Rahmandad and Sterman, 2008; Young, 2009). For the heterogeneous view, the adoption rate that generates the curve is based on different characteristics of individuals, and for the homogeneous view the process of communication is the primary driver.

First, the homogeneous perspective is reviewed. The homogeneous approach is best described by an aggregate or macro-level method to analyzing diffusion (Rahmandad and Sterman, 2008). This top-down modeling framework explores diffusion in terms of the overall market without explicitly considering different interactions between individuals. The aggregate framework is exemplified by the Bass model, which has been applied extensively for modeling and projecting innovation diffusion (Bass, 2004).

Next, diffusion in terms of a heterogeneous population is considered. In this setting, potential adopters are explicitly characterized according to different traits. The factors include details such as income and education level. For example, knowing the size of the home also suggests the number of solar panels installed on each home (Islam and Meade, 2013). Such characteristics may influence the decision to adopt as well as the degree of use, which lends analysis to a bottom-up approach (Rahmandad and Sterman, 2008).

The micro-level concept focuses on sources of heterogeneity and interactions between potential adopters to determine the rate of adoption (Peres et al., 2010). Agent-based modeling is the predominant method for managing decisions at the individual level, and for applying connections and system characteristics to exemplify group behavior (Kiesling et al., 2012).

Scenario development is often necessary to accommodate uncertainty in assumptions in order to produce diffusion forecasts. Macro and micro models provide structure, but making adjustments to key influences in the model is important for illustrating different outcomes. Development of scenarios integrates well within the CLCA framework. As described by Zamagni et al., CLCA results are driven by scenarios, where a sequences of events lead to a final assessment

(Zamagni et al., 2012). The purpose of consulting diffusion of innovation research is to bring better understanding to potential adoption mechanisms and provide the most credible scenarios according to available data.

2.6.1 Macro-level Diffusion Models

The basic method to describing diffusion of innovation at a macro-level is derived from differential equations (Rahmandad and Sterman, 2008). The aggregate modeling approach is considered through parameter estimation for functions that use time as an independent variable. Aggregate models are advantageous in that they are a concise representation of the diffusion process; however, there are important limitations in their ability to project outcomes and to provide insight to underlying processes (Parker, 1994). The Bass model is the most widely used aggregate diffusion model (Peres et al., 2010).

2.6.1.1 Bass Model

The objective of the Bass model is to predict successive number of adopters of durable goods using parameters derived from earlier adoption data or from adoption of analogous technologies (Bass, 2004). The population is considered in terms of innovators and imitators. Diffusion is initiated by innovators who adopt through independent motivations. As greater numbers of innovators adopt, imitators become increasingly interested in the technology and begin to accelerate diffusion. Once the technology saturates the market, the number of potential new adopters diminishes, ultimately terminating diffusion. A conceptual illustration of the Bass model is shown in Figure 2.2 according to the number of adopters at a given time.

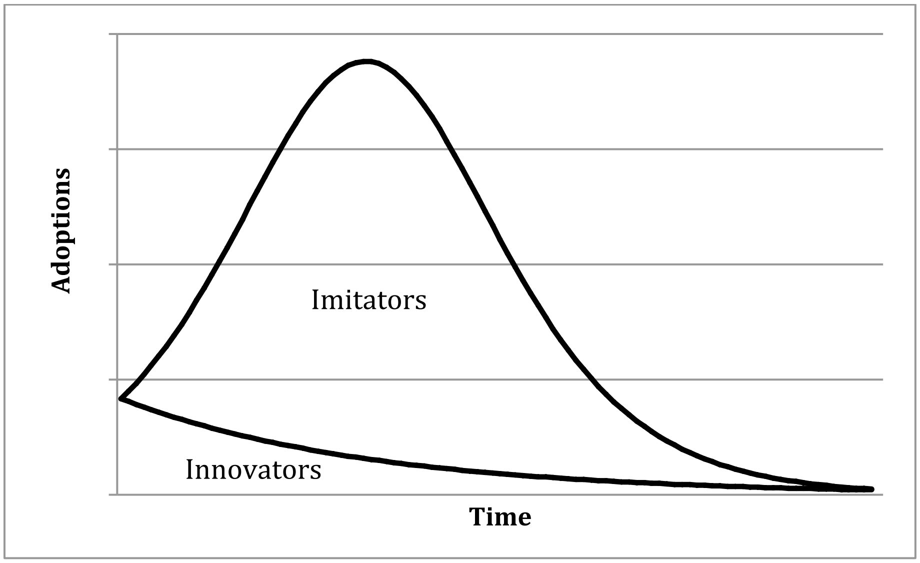


Figure 2.2 Conceptual Illustration of Bass Model for the rate of Adoption. Adapted from Mahajan, V., Muller, E., Bass, F.M., 1995. Diffusion of New Products: Empirical Generalizations and Managerial Uses. Marketing Science 14, G79–G88.

The adoption curve is modeled by the three parameters *p*, *q*, and *m*. The first two parameters indicate the relative influence of innovation and imitation, respectively, and *m* represents maximum adoption. The inter-relation between *p* and *q* suggests the degree of initial intrinsically-driven adoption relative to influence gained through communication channels. The original Bass model is

$$f(t) = \frac{(p+q)^2}{p} \frac{e^{-(p+q)t}}{(1+\frac{q}{p}e^{-(p+q)t})^2}, \quad (1)$$

where *f(t*) represents the number of adopters added at time *t* as depicted in Figure 2.1, *p* ranges from values of approximately 0 up to 0.03, and *q* is typically between

0.3 and 0.5 (Mahajan et al., 1995). Integrating Equation 1 with respect to t provides a cumulative adoption view, which reflect an S-shaped curve.

An advance to the Bass model is an approach that allows exogenous variables such as price and advertising efforts to be incorporated into Equation 1. Aside from using just two parameters to describe the shape of the adoption curve, a variety of other variables can be considered in the generalized Bass model (GBM) (Bass et al., 1994; Ruiz-Conde et al., 2006). Equation 1 is converted into the generalized form by replacing t with a function $X(t)$ where exogenous or external influences that change over time can affect diffusion.

By segregating adoption according to two forces, the Bass model can provide additional insight over other aggregate models. The p and q parameters have also been described as representing external and internal influences, respectively (Bass et al., 1994; Peres et al., 2010). External influences are those that trigger adoption aside from social contagion (Mahajan et al., 1990). Internal influences may largely be motivated by word-of-mouth or social contagion effects, which influence or discourage adoption based on actions of others. The distinction between these sources of influence is useful for determining the projection capabilities of the Bass model (Hauser et al., 2006).

A recent application of the Bass model studied early stages of wind energy diffusion within states in India (Usha Rao and Kishore, 2009). The study considered the relationship between p and q estimates to inform potential incentive policies tailored to each state. The authors fit the Bass model to expansion of wind energy for Indian states and compared fitted values for p and q between states. Relatively small p estimates suggest a lack of success in terms of upstart actions in wind innovation. Targeting extra support for nascent efforts in developing wind energy could boost wider diffusion. States with relatively low q values indicate potential to facilitate imitation by supporting better communication of wind as a viable option.

The wind energy diffusion application can be considered in conjunction with estimating net greenhouse gas (GHG) impacts of wind energy. Consequential LCA results can show which states have background energy systems with higher GHG emissions. A CLCA can also help determine locations that are best suited for wind power infrastructure and energy production that minimize environmental impact. Through various scenarios, CLCA findings coupled with the Bass model can provide comprehensive evaluation for optimizing policy that target reduction of GHG emissions as opposed to general promotion of wind energy.

Photovoltaic (PV) solar diffusion within and across several different countries also exemplify the interaction between p and q and reveal shortcomings for using GBM as a predictive tool (Guidolin and Mortarino, 2010). For more mature solar markets with longer history of data, GBM forecasts performed well (Guidolin and Mortarino, 2010). Two methods of invoking external influences were imposed in terms of different forms of policy. For countries with a shorter PV history, projections of adoption were significantly different depending on the methods used to incorporate policy (Guidolin and Mortarino, 2010). Such assessments indicate the difficulty in forecasting systems for which little historical data are available.

Photovoltaic technology has also been the subject of several LCAs and prospective LCAs (Azzopardi and Mutale, 2010; Bhat and Prakash, 2009; Pehnt, 2006; Stoppato, 2008). Effective utilization of PV options depends on prospective technological advances, integration within existing energy systems, and location (Raugei and Frankl, 2009; Strobel et al., 2009). These factors not only complicate scenarios for CLCA, they also affect PV diffusion. Weak social contagion effects may limit diffusion, or it may be limited by other factors such as material constraints that are brought to light from performing CLCA of PV. As with the wind energy example, effective reduction in environmental impacts such as GHG emissions depends on what energy systems are displaced. Analysis of potential adoption alongside CLCA scenarios can, for example, suggest that regions where PV displaces coal-fired power can compensate for factors that limit efficient PV utilization.

Case studies using the Bass model illustrate the potential for projecting adoption using aggregate diffusion models. The studies also indicate possible influences for the rate of adoption at different stages of the diffusion cycle. However, in terms of projecting total environmental impact, a primary concern is predicting the extent of adoption. For systems in the early stages of adoption, data from which to forecast is limited and straightforward application of the Bass model for forecasting purposes offer little reliability. Heeler and Hustad (1980) analyzed diffusion of several different durables within many different countries. They used the Bass model to estimate the year of peak adoption and the magnitude of adoption for that year with four, six, and eight years of data (Heeler and Hustad, 1980). With over 30 case studies, they demonstrated that predictive capabilities of the Bass model, especially with few years of data, are limited (Heeler and Hustad, 1980). The error in forecasting peak year and adoption is echoed by other reviews that suggest a primary use for the Bass modeling is descriptive rather than predictive when data are short supply (Mahajan et al., 1990; Parker, 1994).

2.6.1.2 Managing Data Limitations for Aggregate Diffusion Models

Two general avenues to achieve useful diffusion results for innovations with limited historical trends include applying data from analogous systems and using statistical techniques to more deeply explore relationships between adoption and external influences (Daim et al., 2006; Kesidou and Demirel, 2012; Sood et al., 2009; Sultan et al., 1990). Meta-analysis entails gathering data across studies and applying results to a system of interest. For example, one study examined 30 product categories to make general conclusions about the duration for different stages of the diffusion process (Golder and Tellis, 2004). For forecasting market penetration, meta-analysis is exemplified using a Bayesian statistical approach. For examining relationships between external influences and adoption, regression analysis is the main focus; other methods such as hazard models have also been used (Golder and Tellis, 2004).

Bayesian Analysis. Bayesian statistical methods offer a succinct structure for incorporating meta-data or previously acquired observations (Gelman et al., 2002). Bayesian inference considers prior knowledge as part of developing statistical conclusions based on a set of observations. As new observations are available, data are conveniently incorporated into analysis through the posterior distribution of parameters. In the same way, diffusion data from analogous systems inform a prior distribution for parameters of an aggregate model. As adoption data for the innovation of interest becomes available, estimates are updated to reflect appropriate uncertainty between prior expectations and posterior results.

An example of a Bayesian approach was applied to the Bass model where parameter distributions were generated according to data on seven different durable goods (Lenk and Rao, 1990). Despite differences between the innovations considered, the amalgamation of data offered useful predictive capabilities for Bass model parameters of a given product (Lenk and Rao, 1990). Another application of the Bayesian-Bass model approach used internet access and mobile telephone diffusion in different European countries (Van Everdingen et al., 2005). By utilizing prior data, the Bass model produced better forecasting results in the early stages of diffusion for countries that have yet to have innovations take off (Van Everdingen et al., 2005).

Bayesian analysis is useful for applications with limited information on adoption of an emerging innovation but where data for similar technologies within other systems are available. With the goal to estimate market penetration to calculate overall environmental impacts, utilizing Bayesian analysis in an aggregate model setting can avoid the tedious analysis of separating influential components that may expose the model to further error. Attempting to isolate the degree that particular influences shape diffusion may lead to incorrectly weighting factors that offer little contribution while failing to include important characteristics that may have much stronger relationships to adoption. Instead, when applying Bayesian methods to aggregate diffusion models, the challenge is to acquire data from analogous diffusion system that are fitting to the socio-technological conditions and the characteristics of innovation.

External Influences. Exploring the role of external influences versus that of social contagion in diffusion modeling may offer beneficial information for adopter motivations (Van den Bulte and Stremersch, 2004). Straightforward application of aggregate models offer little insight to the predictive processes underlying adoption (Parker, 1994); however, closer investigations of adopter influences within such models can reveal useful relationships.

Determining constraints to market penetration can provide answers as to extent of diffusion (Abrahamson and Rosenkopf, 1997). In many cases, innovations of environmental interest are limited by costs, prices of competing technologies, or infrastructure. Understanding the effect of price on adoption can help quantify diffusion potential according to characteristics of adopters. Solar panel adoption is strongly influenced by cost which lead to stronger diffusion estimates and corresponding projections to reduce background carbon-intensive energy systems (Islam and Meade, 2013).

A deeper exploration of adopter motivations further indicates that influences to adoption shift according to the stages of diffusion. Regression analysis applied to systems such as the fuel cell buses example could offer additional insight to diffusion potential. Adoption response according to different influences at different points in the diffusion process can help identify environmental consequences. From a demand perspective, bus adoption is assumed to be initially constrained by cost (Sandén and Karlström, 2007). Supply constraints may dictate market penetration in latter stages of diffusion, which could initiate second order environmental effects (Sandén and Karlström, 2007).

Prior to a product reaching the growth stage of diffusion, network effects may actually dampen the initial expansion of innovation because many adopters wait on others to adopt first (Goldenberg et al., 2010). The reluctance to shift to new technology could be more broadly interpreted as path dependency (Arthur, 1994). An initial release of an innovation has little momentum from social contagion to drive diffusion, and simultaneously there are barriers when abandoning the status quo. Reaching a point for which diffusion of the innovation begins to accelerate instead entails a complex alignment of circumstances and external factors (Arthur, 1989; Gladwell, 2006; Golder and Tellis, 1997). As an innovation overcomes the initial inertia and begins to rapidly diffuse, the product enters the growth stage where interaction between consumers then play a more prominent role (Peres et al., 2010). The final stages of diffusion entail a transition to an additional set of influences. The network effects eventually give way to market saturation, a new wave of technology, or another set of exogenous factors that limit adoption (Parker, 1994; Islam and Meade, 1997; Meade and Islam, 2006).

A variety of regression techniques have been used to analyze factors of adoption that are not related to internal network effects, but instead focus on external factors that influence adoption at an aggregate level. A straightforward example considers the association between housing starts and washing machine sales (Mahajan and Peterson, 1978). Another example includes general economic factors, such as gross national product, to assess potential sales of durables (Deleersnyder et al., 2004).

Gathering information regarding external influences merit inclusion in projections of environmental effects, especially as price and policy are often key limitations of market penetration and economic feasibility of emerging innovations (Lund, 2006). Many applications consider policy effects on adoption of various energy technologies (Horbach et al., 2012; Jansson et al., 2010; Johnstone et al., 2010; Popp, 2010). Combining CLCA results with analysis of diffusion for these emerging energy innovations improves assessments of policy aimed at reducing environmental impacts.

Examining external factors that influence adoption often reveal the heterogeneous nature of adopters where individuals react to influences differently (Emmanouilides and Davies, 2007; Peres et al., 2010; Rahmandad and Sterman, 2008). The role of influences such as income, education, and propensity for risk imply different rates of adoption which lead to more detailed modeling (Islam and Meade, 2013; Peres et al., 2010; Rogers, 1995; Song and Chintagunta, 2003; Van den Bulte and Stremersch, 2004).

2.6.2 Micro-level Modeling

Diffusion of innovation analysis at the micro-level involves examining behavior according to heterogeneous individual adopters (Chatterjee and Eliashberg, 1990; Laciana et al., 2013; Parker, 1994). The adoption curve is generated by totaling choices of individuals who adopt over time as opposed to approximating market diffusion according to an overarching equation. There is potential for emergent insight by viewing shifts in social behavior as a result of incremental choices at the micro level (Schelling, 2006); however, such level of detail also require more effort in designing simulation as well as data collection for describing decision rules and network structures. A sophisticated bottom-up model can represent realistic interactions within the diffusion process (Goldenberg et al., 2010; Rahmandad and Sterman, 2008).

Returning to the residential solar panel example, characterizing adopters may be useful. Cost of solar energy is an important aspect adoption, but diffusion can also be framed in terms of home location and income (Islam and Meade, 2013). This information can capture the propensity to adopt along with the degree of adoption for particular heterogeneous categories. Projecting from these additional pieces of information highlights the potential for residential solar power generation in terms of home size, electricity generation profile, and possible clusters of adoption – all of which may be useful in aggregating CLCA results.

Agent-based simulation is the preeminent tool for modeling innovation diffusion according to individuals or firms (Peres et al., 2010). Agent-based modeling (ABM) uses software to define a stochastic decision-making structure for individuals or firms within a simulated network. Through a time-step process, agents interact and make choices according to initial conditions and constraints. Three central strengths to ABM are the representation of realistic behaviors of individuals and social patterns, the examination of the system for emergent activity, and the flexibility to adjustments of network and agent conditions (Bonabeau, 2002). The appeal of ABM is seen in increased interest from diffusion researchers as indicated by breadth and number of recent ABM applications (Goldenberg et al., 2010; Kiesling et al., 2012; Laciana et al., 2013)

ABM is well-suited to analyze and project diffusion behavior according to adopter heterogeneity and according to social influences (Kiesling et al., 2012; Laciana et al., 2013). By accounting for the difference among adopters, analysis may bring more insightful projections for what technologies are replaced and the degree to which each adopter utilizes an emerging innovation which are useful for ascertaining estimates of net environmental changes. Also, using simulations often allows for convenient implementation of what-if scenarios to accommodate uncertain assumptions and potential system perturbations such as from policy or technological changes (Kiesling et al., 2012). Depending on available data for potential adopters, communication networks and environmental effects of interest, ABM may be an appropriate alternative to the Bass model when coupling with CLCA.

2.6.2.1 Agent-Based Modeling Implementation

To implement ABM for modeling diffusion of innovation, the decision to adopt or not adopt for individuals at each time step is motivated from two perspectives. One source of influence depends on characteristics of the individual adopter. Agents are given a set of traits that include risk aversion, income, age, education, utility, and so on that are intend to match key factors of the actual population. Secondly, the topology of the social network is then arranged to mimic communication channels, connections, and potentially the physical location within the study area (Bohlmann et al., 2010; Delre et al., 2010; Berger, 2001). The simulation records actions of agents that behave according to decision rules based on their location within the social network.

Within the ABM framework, details of the model can be arranged to fit actual circumstances and to investigate the key interests of the socio-technological system. To take advantage of the dynamic nature of the agent-based model, the price of the innovation may change over time for example, which can affect the propensity to adopt for some or all agents (Kiesling et al., 2012). Or, agents may be designed such that they transition through a number of states as opposed to a simple binary code for adoption. One instance considers four states according to adoption status as well as receiving positive or negative word-of-mouth communication (Goldenberg et al., 2007). In this example, agents can change status based on communication before adopting.

The arrangement of agents within the network can also affect adoption outcome. Communication that emanates from hubs or agents that are arranged in close proximity or connection clusters may be important for how an innovation spreads over time or fails to diffuse to segments of the population (Delre et al., 2010; Goldenberg et al., 2009; Kempe et al., 2005).

The key challenge in implementing ABM is acquiring adequate data to properly characterize and condition agents. Further data may also be necessary to organize the network and include other possible external factors that may influence communication and adoption within it. As with aggregate models, historic behavior with analogous innovations provides general guidelines for the spread of information and adoption (Vespignani, 2009). Regression analysis again indicates adoption patterns according to particular external variables. Furthermore, ABM can accommodate survey results. Survey data can include demographic data or other variables of interest to illuminate particular behavior interactions and to inform agent decision rules (Kaufmann et al., 2009; Kiesling et al., 2012).

2.6.2.2 Agent-Based Modeling of Environmentally-oriented Applications

As with the original fuel cell bus example, the ABM results also can indicate potential for drastic shifts in transportation with this type of technology. The ABM model could detail the effects of infrastructure and filling stations on adoption. Exploring the diffusion process in this way would help to ensure all relevant components are included in CLCA. In estimating the overall impacts of fuel cell vehicles, a CLCA also must include the accompanying construction and operation of a hydrogen-based infrastructure.

An exploratory investigation of market penetration of plug-in hybrid vehicles considered the potential impact of a number of variables on diffusion in the U.S. To describe the heterogeneity of adopters, income and annual vehicle miles traveled were used to shape probabilities of adopting (Eppstein et al., 2011). Spatial effects and social interactions were considered as part of the network structure, and external influences such as gasoline price and battery range were analyzed as global impacts to vehicle utility (Eppstein et al., 2011).

To assess the expected net environmental impacts of many technologies, the degree to which adopters utilize the new innovation may be an important consideration. When considering plug-in hybrid vehicles for example, the reduction in GHG emissions not only depends on the source of electricity, but also on what type of vehicle is replaced and how the plug-in hybrid vehicle is used. Adopters who replace fuel efficient cars and live in areas that generate electricity from coal have less effect on GHG emissions than those who are able to optimize the vehicle's electric mode and live in areas with nuclear power. Such considerations are necessary for projected CLCA results.

A survey in southern Germany informed an ABM of diffusion of water-saving technologies (Schwarz and Ernst, 2009). Regression analyses were performed on survey results to designate the degree that different factors shape the decision process for each technology (Schwarz and Ernst, 2009). The empirical portion of the paper allowed for clustering agents according to five lifestyle definitions such as postmaterialists, social leaders, traditional, mainstream, and hedonistic (Schwarz and Ernst, 2009). The authors were then able to correlate adoption between the lifestyle groups with five innovation characteristics such as environmental performance, ease of use, cost savings, compatibility, and investment costs (Schwarz and Ernst, 2009). This study shows the potential for using survey data to inform decision rules, which ultimately help estimate market penetration for technologies with little historical trends from which to forecast.

A final example considers residential combined heat and power (micro-CHP) for the Netherlands (Faber et al., 2010). The authors highlight the greenhouse gas and NO_x emissions improvement with CHP over background systems (Faber et al., 2010). There remain significant uncertainties about the potential effectiveness of micro-CHP technology as more efficient systems may improve emissions estimates in terms of an order of magnitude (Faber et al., 2010). Market penetrations of 50%

is used for demonstration purposes, which highlights that the bulk of uncertainty for net environmental impact rests with projected LCA estimates as opposed to diffusion modeling results.

2.6.3 Summary of Applications for Macro and Micro Models

On one hand, the macro-level method as exemplified by the Bass model is a concise representation of diffusion that requires few parameters to estimate. The extensive use of the Bass model and adaptations confirm its effectiveness to capture general behavior and market potential without requiring an abundance of data. The Bass model illustrates general effects with a low resolution and does not lose sight of the overall diffusion progression (Bass, 2004; Laciana et al., 2013; Parker, 1994; Ruiz-Conde et al., 2006).

On the other hand, the Bass model assumes a homogenous population which lead to important shortcomings (Bohlmann et al., 2010; Parker, 1994). In some cases, a bottom-up approach that explicitly accounts for different characteristics of individuals as well as connections within the network structure may be more appropriate. Though ABM is a common approach to heterogeneous data sets, gaining information on adoption behavior likely entails a variety of modeling angles (Meade and Islam, 2006). Survey analysis, regression modeling, and cost-benefit analysis are options that may work in conjunction with establishing ABM conditions or used independently to examine how segments of population might behave (Goldenberg et al., 2010; Kiesling et al., 2012).

Circumstances and objectives to an assessment determine which method is most appropriate. Gathering data from surveys is an option when disseminating a questionnaire is convenient and when there are few options for applying data from analogous systems. Regression analysis is useful for determining possible associations between adoption and other trends that are forecasted more effectively. For example, if the cost of a new innovation is strongly related to adoption potential, projected changes in costs can then be used as an explanatory variable to strengthen rate of adoption forecasts. Incorporating the benefit in relation to costs can further advance an analysis. The length of the payback period, for instance, may generate more explanatory power for the rate and extent of diffusion.

For effective diffusion of innovation analysis when estimating total environmental impacts associated with emerging technology, assessments should be performed early in the diffusion process or prior to launch in a new area. Findings of projected environmental outcomes can guide policy and adopter decisions. Implementing changes becomes progressively more difficult once major investments have been made and a technology is increasingly established (Parker, 1994; Schilling and Esmundo, 2009). This implication adds analytical and data challenges for forecasting diffusion of environmentally-oriented innovations.

Bayesian methods, regression analysis, and surveys are possible ways to strengthen diffusion analysis; however, when applying any type of innovation diffusion method prior to the launch of a technology, there are enormous uncertainties and assumptions. One approach is to consult a number of appropriate specialists to help frame ranges for forecasts and learn of factors that have strong leverage for affecting outcome. Analysis of expert opinions are also able to provide effective forecasting results (Landeta, 2006). In some circumstances, intuition provided by managerial experience can validate or improve diffusion projections by making appropriate projection adjustments that are not indicated from the data (Heeler and Hustad, 1980). A final worthwhile step is to perform sensitivity analysis (Börjeson et al., 2006; Rahmandad and Sterman, 2008). By adjusting assumptions or initial conditions, sensitivity analysis can yield additional insight for what factor carry more influence in CLCA scenarios.

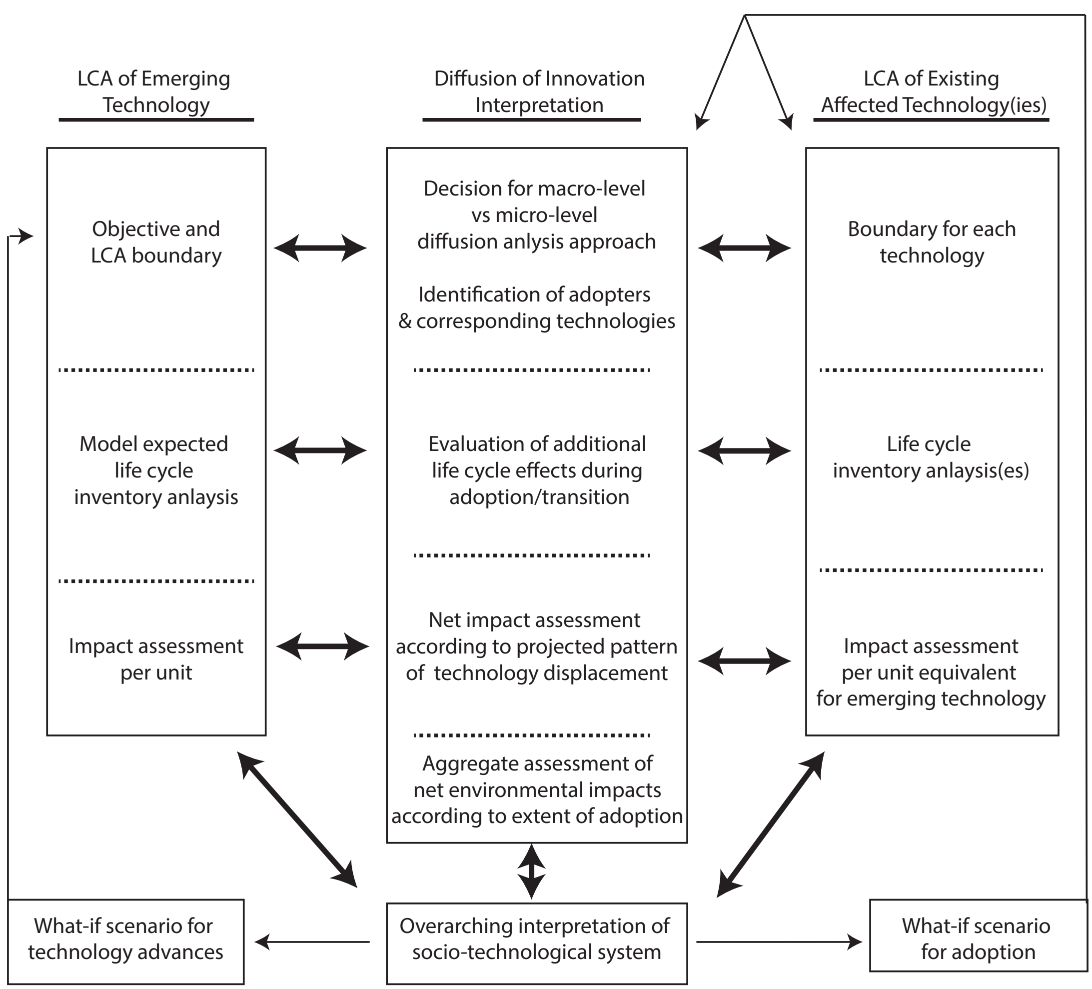


Figure 2.3 Schematic for Integrating Diffusion of Innovation Analysis with Life Cycle Assessment to Aggregate Net Environmental Impacts of an Emerging Technology

2.7 Conclusions

This review explores concepts in diffusion of innovation analysis to project net environmental impacts of emerging technology. The top-down modeling approach is shown by the Bass model, while the bottom-up perspective is exemplified by agent-based modeling. Advantages gained from using either diffusion modeling approach depends on the quality and quantity of relevant data. Information from surveys and experts are potentially useful sources of data. Otherwise, data from prior adoption of analogous systems may provide initial indications for projecting diffusion patterns before significant adoption of an innovation have occurred.

Including economic and social behavior in a prospective environmental analysis introduces layers of uncertainty; however, CLCA scenarios that do not include the broader context limit the capacity to make meaningful conclusions (Sandén and Karlström, 2007). In this analytical framework of emerging technology, developing the most effective and data-supported scenarios is valuable. Moving toward sustainability assessments is inexact, but is necessary for revealing pathways toward dramatically reducing environmental impact (Graedel and van der Voet, 2010; Guinée et al., 2011).

Furthermore, scholars tend to agree that major shifts to technologies that significantly reduce environmental impact require proactive management (Bergek et al., 2008; Berkhout et al., 2004; Foxon and Pearson, 2008; Gallagher et al., 2012; Geels and Schot, 2007; Hekkert et al., 2007; Kemp et al., 2007; Kinzig et al., 2013; Smith et al., 2005). An emerging field focuses on analysis of structures and methods that promote broad application of environmental technologies (Clark and Dickson, 2003; Markard et al., 2012). Managed approaches toward sustainable outcomes may benefit from diffusion-based CLCA which can inform expectations and lead to optimal strategies and to promote the most effective technologies for reducing environmental impact.

A combination of methods from diffusion of innovation and from life cycle assessment can contribute to projections of environmental outcomes of an induced socio-technological shift (Jaffe et al., 2002). Diffusion scenarios for a transition to new technology or set of technologies provide a time frame and estimates of desired integration. Consequential LCAs of the new technologies compared to existing regimes provide estimates of per–unit change for targeted impacts. Using diffusion of innovation concepts to formulate empirically supported relationships may help to optimize pathways by identifying factors that drive adoption as well as likely headwinds.

While no standard process exists for modeling and projecting net environmental impacts for emerging socio-technological systems, an assortment of tools are available that can elucidate sources of influence and gauge possible outcomes. In a rapidly changing world, there is a growing need to better anticipate ecological impacts that emerge from shifts in technological regimes (Assadourian et al., 2013; Notter et al., 2013). To achieve meaningful ecological enhancement for a defined system, analysis of innovations must suggest favorable circumstances and policy that imply significant and well-intended adoption over the long term (Jacobsson and Bergek, 2011). A comprehensive environmental assessment of an innovation is not only based on the reduced impacts per unit, but also on who adopts, what is replaced, and the total number of units that diffuse throughout a region.

3 ESTIMATING MAXUMUM LAND USE CHANGE POTENTIAL FROM A REGIONAL BIOFUEL INDUSTRY

Before applying diffusion models, economic feasibility is addressed from the perspective of farmers in the region. Typically studies provide assessments of profitability as single value in terms of the switchgrass farm-gate price required for breaking even. Such estimates fail to represent the broad range for potential adopters to profit from switchgrass. The proportion of farmers that stand to profit provides an approximation for capacity of adoption. Using switchgrass price as an independent variable, the amount and type of land that breaks even serves as a ceiling for maximum adoption. A breakeven assessment provides a foundation for diffusion of innovation analysis under scenarios of different switchgrass prices.

Though there are some minor formatting adjustments, the remainder of this chapter consists of a journal article accepted by *Energy Policy* in October 2013.

3.1 Abstract

The maximum amount of land for growing switchgrass for ethanol is estimated for a region in the southeastern U.S. Breakeven capacities are calculated for land in row crops, hay, pasture and marginal land. Characteristics of land categories inform potential land use change impacts as well as switchgrass profitability. Variable yields within and across land categories are translated into distributions of switchgrass net revenue. Breakeven curves are generated for a range of switchgrass prices. These curves provide upper bounds for further analysis of actual switchgrass adoption in a context of broader economic forces and possible policy mechanisms to minimize environmental impacts. A farm-gate price of $55

Mg^{-1} is estimated for half of marginal and pasture lands to break even with switchgrass. At this price, only 20% of land in hay and a small fraction of row crop hectares break even. Half of hay and row crops hectares break even at approximately \$90 Mg^{-1} and \$100 Mg^{-1}, respectively. At \$60 Mg^{-1}, sufficient land area can profitably produce switchgrass for ethanol to displace approximately 10% of the gasoline consumed in Georgia, North Carolina, and South Carolina; however, this price only indicates breakeven capacity implying that higher prices is likely necessary to realize 10% displacement.

3.2 Introduction

Examining probable diffusion patterns of bioenergy crops provides insight for optimizing resources, and for identifying unintended consequences in terms of potential system changes, environmental impacts, and policy direction (National Research Council, 2011; Jaeger and Egelkraut, 2011; Jensen et al., 2011; Searchinger et al., 2008; Fargione et al., 2008; Hoekman, 2009; Kim et al., 2009). Although multiple sources of uncertainty emerge when projecting effects of land use change (LUC) due to the expansion of bioenergy production, useful information can be obtained regarding bioenergy potential within a region (Curtright et al., 2012; McKone et al., 2011; Williams et al., 2009). The objective of this work is to establish an economic basis for estimating the maximum potential land available for a proposed switchgrass-to-ethanol system for the southeastern U.S. The proposed breakeven methodology segregates sources of uncertainty and incorporates land variability to assess expected switchgrass profit. This preliminary study of economic capacity can be integrated into comprehensive evaluations of regional switchgrass adoption and consequential environmental impacts. Such assessments take into account the direct advantages of a new technology as well as the effects of who adopts, what is replaced, and the extent that an innovation diffuses throughout a region (Gallagher et al., 2006; Rogers, 1995).

A number of studies have investigated profitability of growing dedicated perennial grasses for energy (National Research Council, 2011; Boyer et al., 2013; Perlack and Stokes, 2011; Mooney et al., 2009; Miranowski and Rosburg, 2010; Landers et al., 2012). My work distinguishes among different land uses and their variability to profit by converting to bioenergy crops. I assess the type and the quantity of land that is economically feasible for a range of switchgrass prices rather than a single breakeven estimate. Taking into account distributional information is a useful perspective when forecasting because outcomes of a proposed system are likely to fall within a range of values provided by prior analogous systems (Flyvbjerg, 2008). A distributional context also offers useful detail in terms of land-specific market penetration (Khanna et al., 2008; Myhre and Barford, 2013). Breakeven curves for different land types indicate upper bounds for adoption with respect to switchgrass prices, where breaking even is considered a necessary but not a sufficient condition for land conversion (Myhre and Barford, 2013).

This analysis maintains simplicity in accordance with the degree of industry uncertainty while retaining the ability to modify key assumptions. The potential capacity for switchgrass production may change dramatically depending on parameters related to revenue and cost for both switchgrass and baseline land uses. Deviations in expected commodity prices and switchgrass performance are considered. Furthermore, this research briefly examines historical patterns of resistance to land use change where land is not converted despite apparently greater profits posed by other options (Barr et al., 2011; Swinton et al., 2011).

3.2.1 Background

The states of Georgia, North Carolina and South Carolina share similar agricultural traits and limited exposure to biofuel production. They have also been identified as areas with potential to supply significant cellulosic biomass through perennial grasses as part of the meeting goals of the U.S. Renewable Fuels Standard (RFS) by 2022 (US DOE, 2011; USDA, 2010). The Southeast offers a relatively long growing season as well as several possible sources of cellulosic feedstock such as switchgrass, miscanthus, mill residues, urban waste, and timber (Evans and Cohen, 2009; Somerville et al., 2010). Switchgrass is considered because it has been investigated extensively and supported by a number of studies as a bioenergy source (McLaughlin and Adams Kszos, 2005; McLaughlin, 1992; Mitchell et al., 2008; Sanderson et al., 1996; Schmer et al., 2008; Wright and Turhollow, 2010). In addition, switchgrass is representative of other perennial grasses such as miscanthus, and is chosen due to lower establishment costs (Khanna et al., 2008). Woody biomass and other sources may also supply cellulosic material; however, the current study focuses on switchgrass due to its potential to impact land use change (Chamberlain et al., 2011; Parrish and Fike, 2005; Sarkar et al., 2011).

Switchgrass is a native perennial grass known for drought tolerance and deep roots (Frank et al., 2004; McLaughlin and Adams Kszos, 2005). Several studies have discussed the benefits of switchgrass as a biofuel feedstock including high biomass yields with relatively little agricultural input (Mitchell et al., 2008; Schmer et al., 2008; Campbell et al., 2008; Miller, 2010; Fike et al., 2006). Switchgrass is often considered over a ten-year planting cycle (Landers et al., 2012; McLaughlin and Adams Kszos, 2005).

Variability in switchgrass yield is utilized along with cost estimates and given prices to project a distribution of profit across the region. A common challenge to approximating the viability of new technologies is translating exploratory-scale evaluations to actual performance for prospective adopters (Qaim, 2003; Spann et al., 1995). Switchgrass has been investigated in terms of possible yields and costs, but harvests will depend on management, weather, and soil quality (Khanna et al., 2008; Haque and Epplin, 2012; Boyer et al., 2012; Larson et al., 2010; Wullschleger et al., 2010; McLaughlin et al., 2006). The distribution of switchgrass yields for trial plots are suggestive of the expected yield distribution throughout the region.

3.2.2 Land Categories

Approximately one quarter of Georgia, North Carolina, and South Carolina is in agricultural land, which includes pasture, woodland, land under the Conservation Reserve Program (CRP), and cropland. This research assumes that USDA designated pastureland and cropland are the only areas that will be converted to switchgrass in the region. Specifically, the potential of pastureland, marginal cropland, land in hay, and rotated annuals dominated by corn, cotton, soybean and wheat are investigated. Woodland is excluded because direct conversion of woody biomass to cellulosic ethanol is more likely than converting woodland to switchgrass (Somerville et al., 2010). Although CRP has been proposed for switchgrass cultivation for bioenergy

(Perlack and Stokes, 2011; Schmer et al., 2008), it is unlikely to be a meaningful contributor because there is only about 300 thousand hectares of CRP in the region of which most has been converted to timber (USDA NASS, 2013; Petrolia and Ibendahl, 2008).

Land in row crops is represented by corn, soybeans, cotton, and wheat covering approximately 85% of harvested annual crops in the region (USDA NASS, 2013). These crops are aggregated to quantify profitability because they are frequently rotated which makes distinguishing land by individual crops implausible. Peanuts and tobacco are grown on more specialized farming operations with relatively large capital investments and are not included as part of this analysis (USDA NASS, 2013).

Bermudagrass is assumed to represent all hay due to a lack of data on specific hay varieties. As the foremost forage in the region, it serves as an approximation for all hectares of hay (Anderson et al., 2007; Sanderson and Adler, 2008). Furthermore, bermudagrass has been considered as a possible bioenergy source and has been studied in comparison to switchgrass allowing for convenient yield and cost information (Anderson et al., 2007; Aravindhakshan et al., 2011).

The amount and degree of marginal cropland is not well defined from readily available data (Gopalakrishnan et al., 2008; Mooney et al., 2008). This study uses USDA Census designations for land that is idle, fallowed, and where crops tend to fail (USDA NASS, 2007). Marginal land has been suggested as an ideal solution because switchgrass may succeed where less tolerant crops are not economical while also minimizing impact to food and fiber production (Landers et al., 2012; McLaughlin and Adams Kszos, 2005; Somerville et al., 2010).

Pastureland is also considered for conversion to bioenergy crops (Landers et al., 2012; Mooney et al., 2009; Schmer et al., 2008; Walsh et al., 2003). Pastured cropland hectares are classified in this category.

Land is segregated into marginal cropland, pastureland, row crops, and hay in order to analyze profitability potential under switchgrass. Distinguishing land types also allows for subsequent analysis of expected LUC impacts due to conversion to switchgrass. Land areas are shown in Figure 3.1 according to 2007 Agricultural Census data (USDA NASS, 2013). The respective areas are assumed to remain constant to simplify the analysis, even though cropland has historically declined for this area (USDA, 2013).

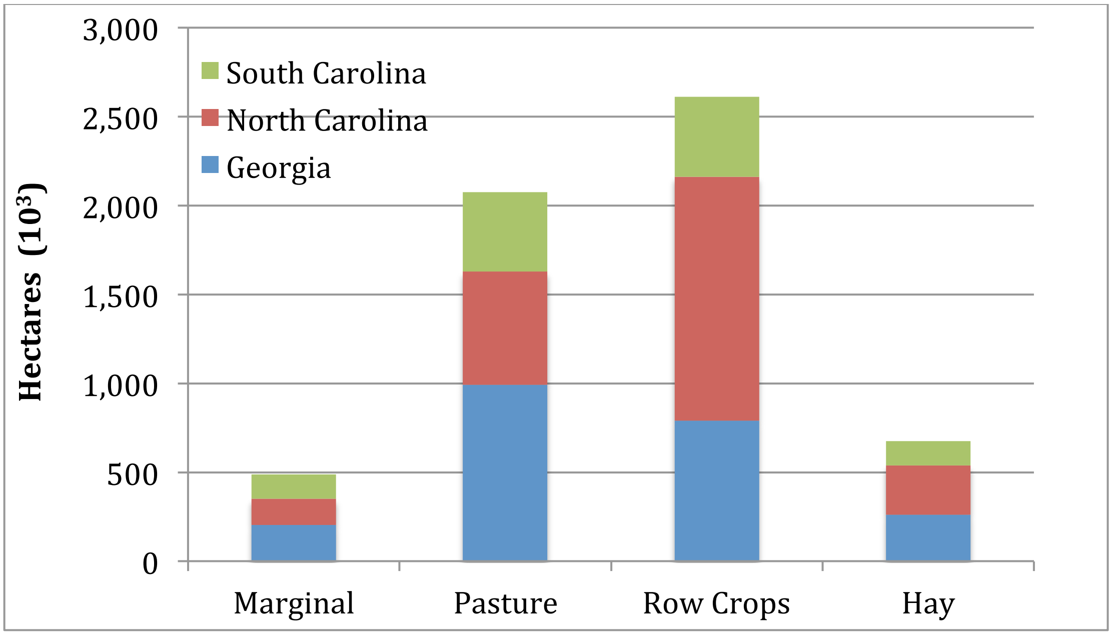


Figure 3.1 Hectares of Marginal Cropland, Pastureland, Four Major Row Crops, and Hay Considered For Switchgrass in the Study Region

3.3 Material and Methods

Breakeven capacity for growing switchgrass in the region is estimated for each category according to uncertainty of markets and agricultural performance. For all land uses, costs and net revenue are estimated in terms of annual dollars per hectare as applied over a ten-year period. The net revenue generated from existing land uses is defined as the opportunity costs for converting to switchgrass. Farmers are expected to utilize similar evaluations when considering switchgrass as an alternative.

Breakeven capacity is determined by the area of land where switchgrass net revenue exceeds baseline net revenue, or opportunity costs. Because the farm-gate price of switchgrass is a pivotal unknown, price is treated as an independent variable (National Research Council, 2011). Probability density functions (PDF) of switchgrass net revenue are estimated for each price. For other variables, USDA historical data and agricultural estimates indicate expected values as well as associated variation. Net revenues for managed croplands are also assessed using distributions. When comparing net revenue PDFs, switchgrass and traditional crop yields are assumed to be correlated as discussed below. All analyses were conducted in R statistical software (R Development Core Team, 2010).

3.3.1 Estimating Distributions of Net Revenue

Mean yields and standard deviations are considered for each land category along with respective costs and prices. Distributions of expected net revenue (NR) per hectare are calculated from Equation 1.

$$NR = Y \times P - C \tag{1}$$

Yield Y is assumed to follow a normal distribution in terms of annual harvests per hectare for each crop. For switchgrass, the mean and standard deviation is derived from published field trials data. For traditional crops, parameters are estimated from distributions of harvest data generated by average county yields in the region. The projected annual market price is represented by P, and C is the expected annual cost per hectare.

Variability in land quality is assumed to be the major driver determining distributions of net revenue and is captured through Y. There is comparatively limited data for analyzing variability and correlations of costs; consequently, costs are considered invariant, except in the case of comparing switchgrass and hay profitability when yield data are limited. Though yields can be boosted on lower quality land through higher costs, net revenue is reduced. For example, spatially precise measures of nutrient deficiencies can inform economically optimal fertilization rates, yet yields and profits may remain highly variable due to influences beyond management practices (Bullock et al., 2002; Anselin et al., 2004). For row crops and switchgrass, underlying cost strategies are assumed to be overshadowed, and yield distributions serve as comprehensive representation of land quality variation as it pertains to breakeven pricing (Khanna et al., 2008).

Though external influences such as governmental assistance are not explicitly taken into account, opportunity costs incurred while transitioning to switchgrass are considered negligible. Anticipated support such as the Biomass Crop Assistance Program (BCAP) is assumed to compensate for initial costs to convert land to switchgrass.

3.3.2 Switchgrass Estimates

With lowland switchgrass expected to be best suited for the study region, data associated with this ecotype are used (Fike et al., 2006). A truncated normal distribution is fit to a compilation of yield data by Wullschleger et al. (2010), and the resulting parameter estimates of the curve match the overall field trial mean and standard deviation of 12.9 ± 5.93 Mg ha^{-1} (Appendix A Figure A.1). The yield standard deviation is representative of the variability of switchgrass production on hectares throughout the region.

The current study expects marginal land and pasture to have lower yield than managed cropland. Many of the field trials were intended to represent marginal land (Wullschleger et al., 2010). The overall mean from Wullschleger et al.

(2010) is reduced by one Mg ha^{-1} such that switchgrass yield on low quality land is projected to be distributed normally with mean 11.9 Mg ha^{-1} and standard deviation 5.93 Mg ha^{-1}. For managed cropland, the field trial mean is increased by 2.0 Mg ha^{-1} and is projected to follow a normal distribution with mean 14.9 Mg ha^{-1} and standard deviation 5.93 Mg ha^{-1}.

With a projected mean for marginal land that is 80% of that for managed croplands, our estimates correspond to those found in similar studies (Debolt et al., 2009; Walsh et al., 2003). Though other research categorize land differently, average yields used in this analysis fall in the range of published values for approximate land types in the southeast (Boyer et al., 2013; Mooney et al., 2009; Walsh et al., 2003)

Switchgrass establishment and variable costs are estimated from published studies as well as from area extension office budget worksheets. Costs associated with the initial planting of switchgrass are annualized over the ten-year period. An average of compiled annual expenses associated with establishing and maintaining switchgrass is \$625 ha^{-1} per year (See Appendix A Table A.1).

Switchgrass prices are considered over a range from \$0 Mg^{-1} to \$150 Mg^{-1} using \$5 dollar increments. Net revenue is calculated using Equation 1 for each switchgrass price, the cost estimate, and yield distribution. To produce the breakeven curves, a total of 31 net revenue PDFs for switchgrass are generated for each land type.

3.3.3 Estimates for Existing Land Uses

Distributions of net revenue for hectares of the four row crops are also estimated using Equation 1. Normal distributions are fit to average county yields for each crop, which are weighted by county harvested area (Appendix A Figure A.2). Annual costs of producing each crop are averaged according to available farm budgets from area land grant universities (Appendix A Table A.2). Prices used in this study are state-level annual market values weighted according to 2012 state harvests. To capture price trends, ten years of market prices are used to linearly project prices five years beyond the most recent data. A corresponding 90% prediction interval around the five-year point estimates are used to capture uncertainty for these future prices (Kutner et al., 2005). A summary of price, yield, and cost estimates are provided in Table A.3 of Appendix A.

A single representative distribution for the land category is weighted according to each crop's harvested area for 2012. The normal PDF of expected net revenue for hectares of row crops (NR_{crop}) has a mean of \$522 ha^{-1} and standard deviation of \$205 ha^{-1}. The probability of any hectare of row crop breaking even is calculated by Pr($NR_{sg} > NR_{crop}$). The probability is found for each price of switchgrass where NR_{sg} is calculated from the given price, the fixed value for cost, and switchgrass yield which is distributed normally with mean 14.9 Mg ha^{-1} ± 5.93 Mg ha^{-1}. For example, a probability of 0.5 indicates that half the land in row crops is more profitable with switchgrass.

For land in hay, comparable yield data are not available for bermudagrass harvests. Yields are assumed to be similar to those of switchgrass (14.9 Mg ha^{-1} ± 5.93 Mg ha^{-1}). In this case, land quality is represented by variability in fertilizer expenses as opposed to yield. Costs are otherwise assumed to be the same for both grasses because maintenance and harvesting are similar.

I assume that bermudagrass is expected to require twice the fertilizer to match switchgrass yield (Aravindhakshan et al., 2011). Variation of county-level data for fertilizer expenses capture land quality variability. A normal distribution is fit to a histogram of fertilizer expenditures per hectare of cropland based on 2007 Agriculture Census results (USDA NASS, 2013) (Appendix A Figure A.4). This cost distribution is modified to better represent only bermudagrass hectares by adjusting the fitted normal parameters to match the average suggested by regional farm budgets (Appendix A Table A.4). The resulting additional cost for bermudagrass production over that of switchgrass is assumed to be distributed normally with a mean of \$349 ha^{-1} and standard deviation of \$104 ha^{-1}.

The difference between fertilizer costs on hay land is the major driver that determines the distributional effect for breaking even with switchgrass. As with row crops, hay price is projected five years beyond the most recent annual market price and is estimated at \$123 Mg^{-1} (Appendix A Figure A.4). The proportion of hay hectares that breaks even with switchgrass is estimated by the probability that expected net revenue for switchgrass is greater than the expected net revenue for bermudagrass. When switchgrass prices exceed that of hay, essentially all hectares break even because switchgrass is always cheaper to produce and has relatively matching yield.

For pastureland, opportunity costs cannot be appraised directly in terms of net revenue per hectare. The average of annual county rent in the region of 60 ha^{-1}

is used (US DOE, 2011). This single opportunity cost represents all pastureland, and is a similar valuation method used in the Department of Energy's Billion-Ton Update (US DOE, 2011).

Switchgrass on marginal land is assumed to have no opportunity costs and breaks even on hectares that simply generate positive net revenue.

3.3.4 Production Correlations between Switchgrass and Cropland

To more accurately represent potential market penetration, this study assesses approximate correlation values for the distribution of switchgrass yield and traditional crop production. Cropland hectares with lower performance are likely to also have lower switchgrass yields. This relationship is expected to be strongest for hay land due to similar physiology. To illustrate the impact of positive correlation of switchgrass yield with row crop production, Pr(NR_{sg} > NR_{crop}) are plotted according to switchgrass price to illustrate the proportion of land area that breaks even. In Figure 3.2, three different levels of correlation are represented. The breakeven curves are progressively steeper for increasingly stronger relationships between performance of switchgrass and traditional crops. An otherwise uncorrelated assessment would allow greater instances of underperforming land to break even at relatively low prices.

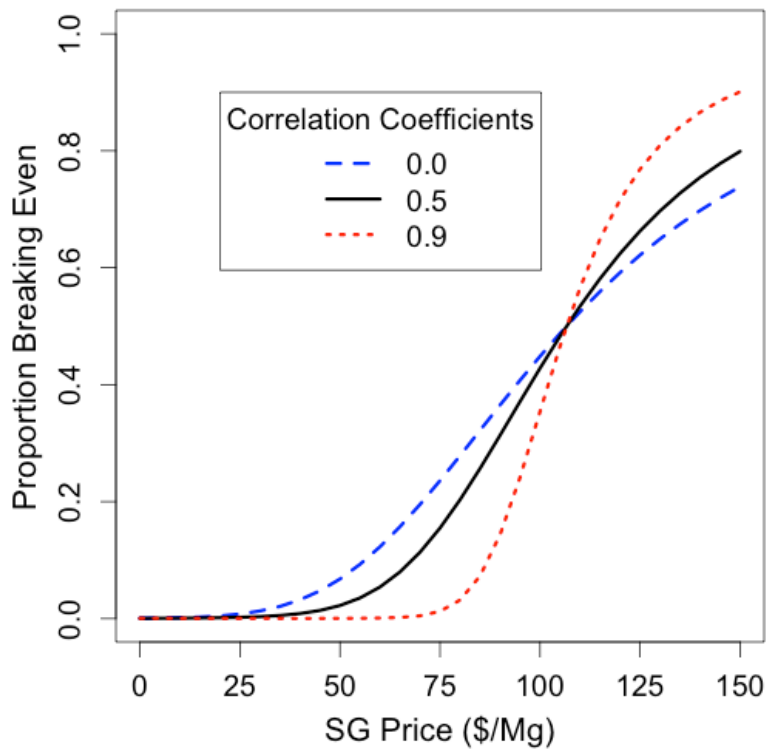


Figure 3.2 Breakeven Proportions of Row Crops according to Switchgrass Price with Three Correlation Coefficients between Switchgrass Yield and Row Crop Net Revenue

Uncertainty associated with correlating switchgrass performance is assumed to be minimal compared to that of yield, cost, and price parameters. Breakeven assessments for land under row crops are performed with a fixed correlation of 0.5 as a compromise of results shown in Figure 3.2. For land in hay, a coefficient of 0.9 is used to reflect the similar production patterns of bermudagrass and switchgrass (Aravindhakshan et al., 2011; Haque et al., 2009).

3.4 Results

The probability that expected net revenue from switchgrass exceeds that of baseline uses is multiplied by the respective number of hectares in the region. The resulting areas are plotted according to switchgrass price to generate breakeven curves. Figure 3.3 illustrates the expected number of hectares that break even by land type and price, and serve as a reference scenario to further evaluate underlying parameters.

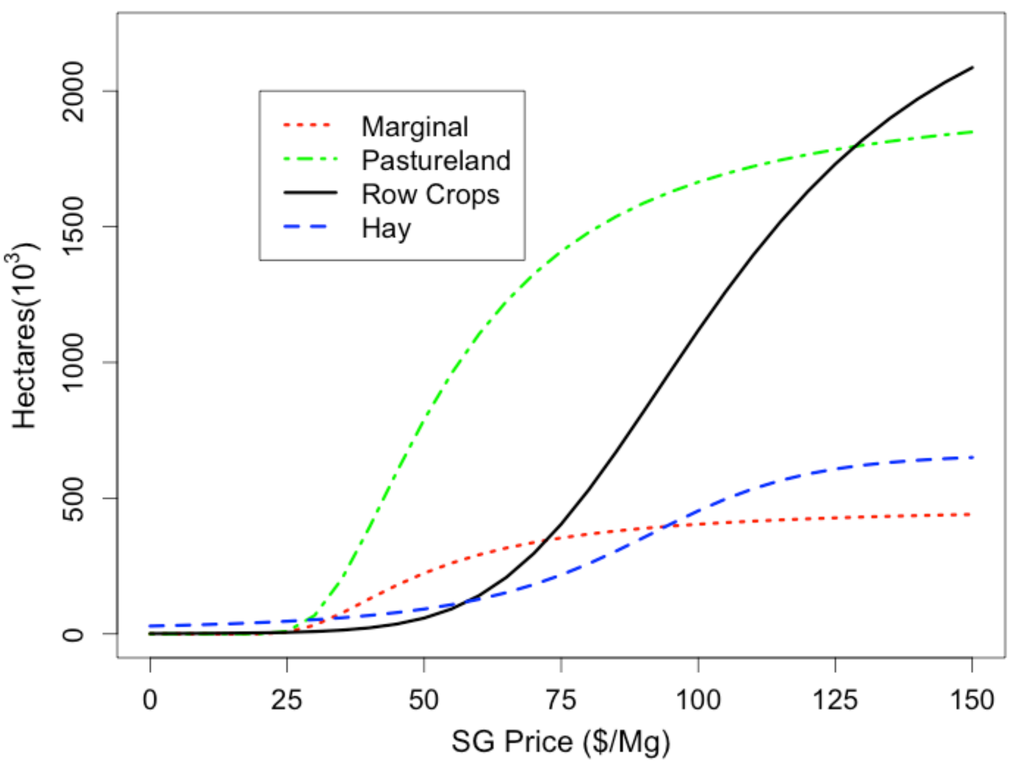


Figure 3.3 Hectares in Study Region that Breakeven according to Switchgrass Price and Land Type

Under the given assumptions, the curves reflect different characteristics associated with switchgrass profitability for each land type. The switchgrass price necessary to break even on half of the land area provides a basis for comparing land types. Pasture and marginal land require approximately \$55 Mg^{-1}, which translates to roughly 700 and 250 thousand breakeven hectares respectively. A total of only 100 thousand hectares of managed cropland are expected to be more profitable at this price. Half of land in hay requires \$90 Mg^{-1}, and around \$100 Mg^{-1} for row crops.

The price projections and high production costs applied to land in hay show that some hectares potentially face significant losses in hay production. With much smaller expenses, switchgrass can be financially favorable at low prices where about 50 thousand hay hectares break even when switchgrass is \$25 Mg^{-1}. For hectares of hay where fertilizer expenses are minimized, switchgrass prices must approach the projected hay price of \$123 Mg^{-1} before breaking even. The large degree of variability estimated for fertilizer costs translates to a comparatively moderate slope to the breakeven curve. A scenario that assumes only a small variance for the difference in costs between switchgrass and hay would result in an abrupt increase in the number of breakeven hectares around \$90 Mg^{-1} because yields are expected to be strongly correlated.

With the projected increase in row crop prices, switchgrass is not more profitable until it exceeds \$50 Mg^{-1}. As prices advance from \$75 Mg^{-1} to \$125 Mg^{-1}, the number of breakeven hectares for row crops jumps by more than a million. This rapid increase in breakeven area emphasizes the impact of higher switchgrass yields for land in row crops. If the correlation used for production were increased or if the estimate for the standard deviation of switchgrass yield were decreased, this curve is correspondingly made even steeper.

The curves for marginal and pasture land have a similar shape. These categories have parallel switchgrass yield expectations and minimal influence from opportunity costs; however, pastureland has significantly more land area in the region. With over 1.5 million hectares, pastureland offers the most breakeven area for switchgrass prices from \$35 to \$100 Mg^{-1}.

Figure 3.3 shows that prices below \$50 Mg^{-1} imply only a relatively small amount of any land is available for switchgrass production. On the other hand, once prices exceed \$150 Mg^{-1} nearly all hectares break even. The steepness of the breakeven curves in between \$50 Mg^{-1} and \$150 Mg^{-1} strongly depend on the extent of variability for profit as it applies to land quality and on the correlation estimates between yields of switchgrass and traditional crops. Scenarios of projected switchgrass performance also affect these observations and are considered in section 3.2.

Industry potential can be assessed by the amount of land required to reduce gasoline consumption by 10% from switchgrass-derived ethanol. The three-state region consumes roughly 12 billion gallons of gasoline annually (EIA, 2011). Factoring in energy density, ten percent equates to 1.8 billion gallons of ethanol and roughly translates to 20 million Mg of biomass. A total area of about 1.4 million hectares is needed to produce this amount of annual biomass. An ideal scenario with complete switchgrass adoption at the breakeven point requires a price of \$60 Mg^{-1} to achieve this total area. The percentages of each land type at \$60 Mg^{-1} are

20%, 61%, 10%, and 9% for marginal, pasture, row crops, and hay, respectively. For actual land conversion to occur, switchgrass prices would likely need to be much higher than expected breakeven estimates (Cundiff et al., 2009). For example, if 25% of farmers who expect to break even adopt switchgrass, a price of \$100 Mg^{-1} is needed to achieve this annual production level. Additional modeling efforts to better understand farmer behavior and decision-making is necessary to properly estimate expected adoption rates as constrained by breakeven capacity (Miller et al., 2012).

3.4.1 Switchgrass Breakeven Studies

Other assessments of switchgrass profit potential often provide point estimates for breaking even. Landers et al. provide a comprehensive evaluation of switchgrass yield and prices for a claypan region of the U.S. Midwest. With switchgrass yields of 12.56 Mg ha^{-1} on four different topsoil depths, estimated breakeven prices for soybean and corn were between \$65 and \$88 per Mg (Landers et al., 2012). The upper end of this range is found according to an opportunity cost estimate of \$465.25 ha^{-1}, which is slightly less than the mean of \$522 ha^{-1} calculated for my study. A breakeven price on claypan soils of \$88 Mg^{-1} corresponds to the midpoint value of \$100 Mg^{-1} estimated for all soils for row crops in the study region.

A study in Illinois accounted for the cost associated with delivery as well as opportunity costs of corn-soybean profits at \$192.76 ha^{-1} (Khanna et al., 2008). Even though the mean value in the current study is much higher than \$192.76 ha^{-1}, the corn-soybean assessment included other costs for delivery and projected lower switchgrass yields. Due to these differences in methodology, the breakeven price estimated at about \$90 Mg^{-1} from Khanna et al. (2008) is comparable to our midpoint estimate for row crop breakeven capacity.

Mooney et al. (2009) examined breakeven prices in Tennessee according to four categories of land, with breakeven points between \$46-\$69 Mg^{-1}. These breakeven calculations took into account a \$168 ha^{-1} cash rental rate (Mooney et al., 2008). A similar study in Oklahoma that considers switchgrass production for electricity generation uses a land rental of \$110 ha^{-1} (Aravindhakshan et al., 2010). Across a variety of trials, it was estimated that a price of \$43.90 Mg^{-1} was necessary to produce and deliver switchgrass (Aravindhakshan et al., 2010). The current study uses a distribution of net revenue rather than land rental estimates as a measure of opportunity cost for land in row crops which is much higher than values reported in these studies. Our assertion is that switchgrass must exceed this representation of opportunity costs as opposed to land rental estimates; consequently, Figure 3.3 shows that managed cropland is expected to require much higher prices for significant breakeven capacity.

Considering this overview of other studies, the results in Figure 3.3 appear to offer reasonable midpoint breakeven estimates, given the variety of economic assumptions and different geographical areas. The slopes of the breakeven curves are useful because they estimate the economic feasibility of switchgrass across a range of prices, which can provide a distributional context for comparisons. Even though my study generally projects much higher crop prices, Figure 3.3 provides comparative insight despite potential opportunity costs discrepancies.

3.4.2 Scenarios for Switchgrass Profitability

Management practices are expected improve such that costs are optimized (McLaughlin and Adams Kszos, 2005; Boyer et al., 2012; Perrin et al., 2008). There has also been discussion regarding yield increases over time as compared with corn (Fike et al., 2006; McLaughlin et al., 2006; Schmer et al., 2008). New varieties along with improved farming practices are anticipated to increase yields (Perlack and Stokes, 2011).

Two separate scenarios are considered. First, switchgrass cost estimates are reduced from \$625 ha^{-1} to \$400 ha^{-1} while maintaining reference yield estimates. In the second scenario, the mean yield for each land type is increased by 25% without a reduction in cost. Figure 3.4 shows land types aggregated to a single breakeven curve for each scenario as compared to the reference case. Figure 3.5 shows results by individual land category.

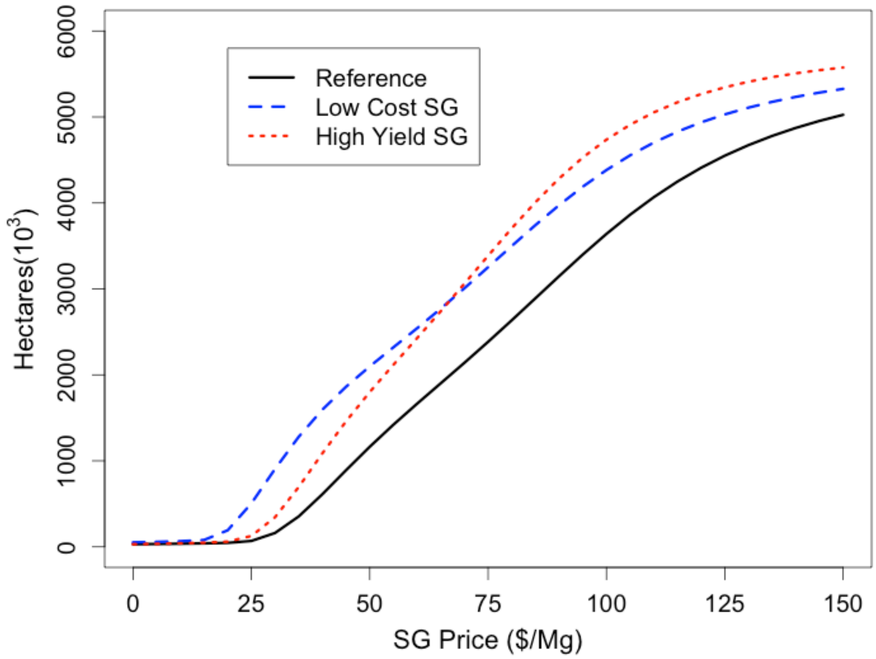


Figure 3.4 Aggregate Breakeven Hectares for Optimistic Switchgrass Scenarios: Low Production Costs and High Switchgrass Yield

The low cost switchgrass scenario allows switchgrass to be more profitable at low prices and especially for land with lower opportunity costs. Significant areas of pastureland are economically favorable for switchgrass prices as low as \$25 Mg^{-1}. The high switchgrass yield scenario taps into a much larger area for switchgrass production on managed cropland. As prices increase beyond \$75 Mg^{-1}, switchgrass rapidly outpaces net revenue of traditional crops adding progressively more hectares to the breakeven area. Generally for all land types, each scenario increased the proportion of hectares to a similar degree for price between \$50 and \$100 Mg^{-1}.

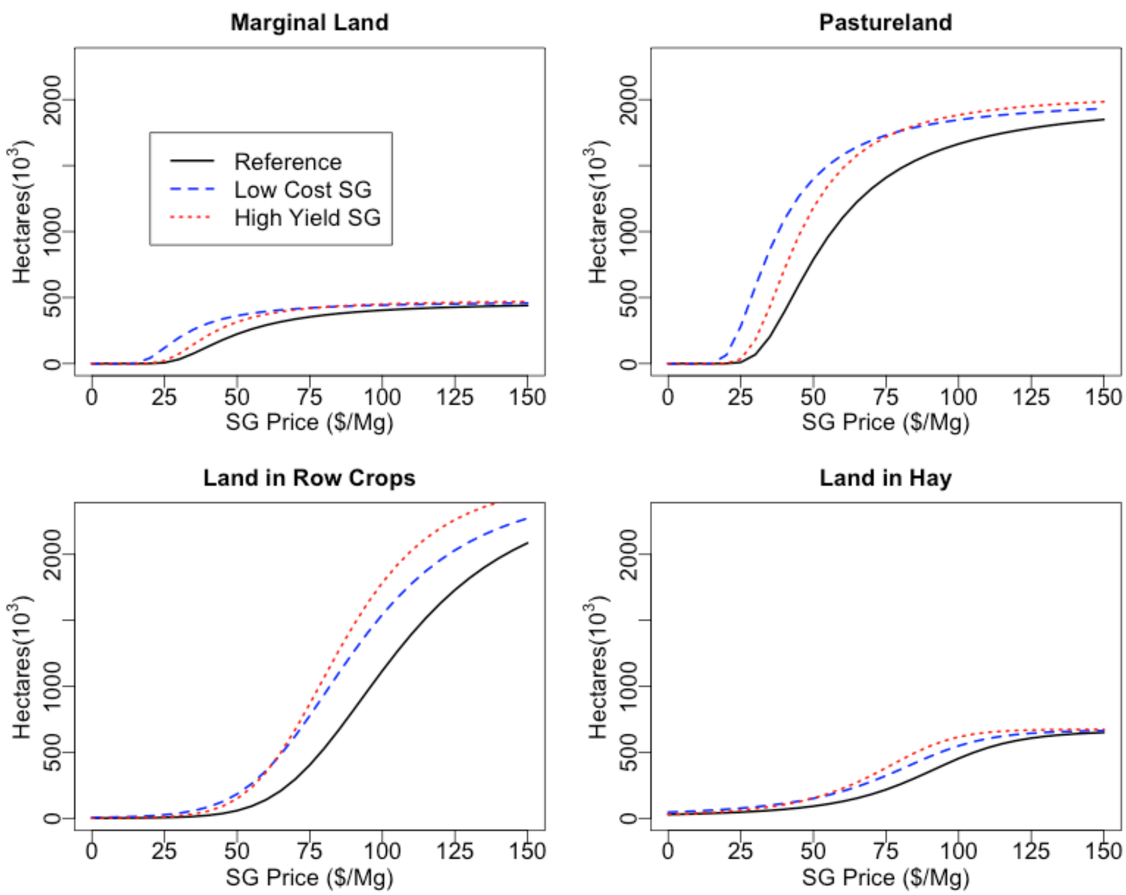
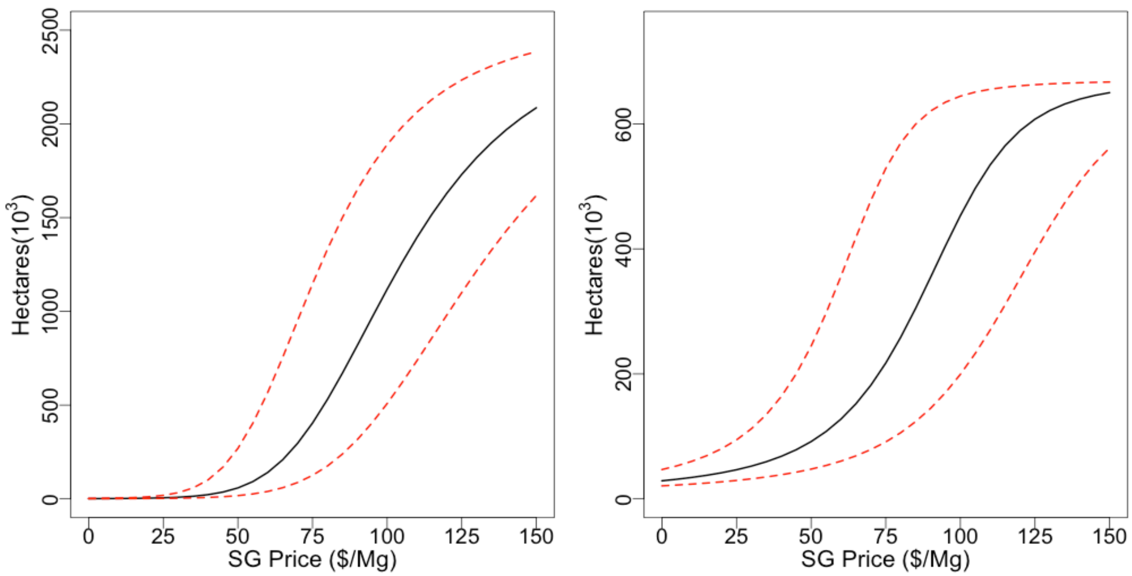


Figure 3.5 Breakeven Hectares for Each Land Category for Switchgrass Scenarios: Low Production Costs and High Yield Switchgrass

3.4.3 Effects of Annual Fluctuations on Breakeven Area of Managed Cropland

Recent data show the propensity for significant shifts in year-to-year net revenue for traditional crops (USDA NASS, 2013). These fluctuations influence the number of hectares that break even with switchgrass for a given season. Using the reference net revenue for switchgrass, the impact of price volatility is assessed for managed cropland. PDFs for managed cropland net revenue are generated from Equation 1, but price P is adjusted to reflect prediction interval limits. Figure 3.6 shows breakeven area for row crops and hay cropland. The bands indicate breakeven capacity according to 90% prediction intervals projected for prices of row crop and hay five years beyond the most recent data (Appendix A Figure A.3 & A.5).



a – Land in Row Crops b – Land in Hay

Figure 3.6 Breakeven Hectares for Both Types of Managed Croplands Using 90% Prediction Interval for Projected Prices

At the low extreme of the crop price prediction interval, switchgrass prices reach half of breakeven area for row crops at about \$75 Mg^{-1}. For the upper extreme, switchgrass must exceed \$125 Mg^{-1}. This price separation is larger for land in hay where half of hay hectares break even around \$55 Mg^{-1} for low hay prices, and \$120 Mg^{-1} for high project prices. These bounded ranges are only representative of price uncertainty and represent the volatility associated with crop markets.

The high degree of uncertainty for opportunity costs presents challenges to estimate the breakeven area for a given year; however, it may also provide an incentive to convert managed cropland to switchgrass. Contract arrangements for switchgrass price as well as potentially steadier production could offer greater stability (McLaughlin et al., 2006). One study incorporated risk in the valuation of converting to switchgrass (Song et al., 2011). A corn-soybean farmer under net present value (NPV) calculations was found to breakeven if net revenue from switchgrass exceed \$259.35 ha^{-1} (Song et al., 2011). Using a real option valuation (ROV) which incorporates risk, net revenue must exceed \$778.05 ha^{-1} (Song et al., 2011). With average yields and cost used in the current study, these different opportunity costs are translated to switchgrass prices. The NPV estimate equates to \$55 Mg^{-1} versus the ROV estimate of \$88 Mg^{-1}. If the switchgrass industry demonstrates greater stability and decreases the risk-derived breakeven price, it may provide additional encouragement to convert cropland to switchgrass. Although, farmers must also forego the opportunity to easily convert switchgrass back to traditional crops when prices are high (Song et al., 2011).

3.5 Discussion

There are useful insights to examining the extent of economic feasibility of switchgrass production by land type. A distributional approach for profitability analysis highlights the notion that potential adopters are not equally suited to switchgrass production. The propensity to profit from switchgrass varies between land categories which has implications for expected LUC impacts. A more complete assessment of LUC potential requires additional work in terms of system dynamics as well as the degree that broader constraints reduce land conversion.

Switchgrass expansion over time implies logistical and market components that also determine the extent of economic feasibility. The proposed breakeven approach could be extended to include more sophisticated techniques for parameter estimation in a dynamic context. Markov Chain Monte Carlo methods may also provide a convenient way to model possible evolution of the industry as markets and production fluctuate. A greater volume of relevant data would merit stochastic processes that could serve as a more robust evaluation of breakeven parameters. Unfortunately, uncertainty regarding the industry's future and the volatility of agricultural markets lead analysis to less precise methods and results.

3.5.1 Broader Considerations toward Switchgrass Adoption

Beyond careful breakeven analysis, there are further barriers to providing practical illustrations of switchgrass diffusion. This work does not estimate the effects of human behavior which ultimately dictate adoption potential. Farmer willingness and land supply elasticity also influence switchgrass diffusion.

Recent studies indicate a significant gap between landowner willingness-to-accept analysis prices and willingness-to-pay valuation, with a difference calculated at approximately $100 (Tyner, 2012). Another study suggests that the costs of converting cellulosic biomass to ethanol entail prices that are not competitive with gasoline (Sainz, 2011). Challenges of efficient conversion to ethanol coupled with willingness-to-accept prices indicate that a combination of governmental support, increased gasoline prices, and technological and agricultural breakthroughs are necessary to advance the industry (National Research Council, 2011).

Additionally, surveys have been conducted in the Southeast to determine factors that affect switchgrass adoption (Jensen et al., 2007; Qualls et al., 2012). At \$44.09 Mg^{-1}, 44.1% of study participants were willing to convert land, and at \$132.28, 52.9% were willing to convert (Qualls et al., 2012). The lack of responsiveness to much higher prices reinforces a ceiling for adoption aside from breaking even. The conversion share for potential adopters further indicates reduction in switchgrass area. At each of the above prices, survey participants that showed willingness to adopt indicated that they would convert on average 33.2% and 38.6% of their land, respectively (Qualls et al., 2012).

In terms of broader economic influences, studies provide evidence of resistance to land conversion (Barr et al., 2011; Swinton et al., 2011). Marginal land has shown limited success for re-entering production. Despite recent increases in crop prices and an overall 64% gain in profitability, there was only a 2% rise in crop planted area (Swinton et al., 2011).

Considering historical data for the three-state region in a similar fashion realizes limitations for pastureland and row crops. Since the 1970s, the proportion of pastureland has remained steady (USDA NASS, 2013). Even with high crop prices, the 2007 USDA Census shows that pastured area as a percentage of cropland was at a relative high point, indicating strong resistance for converting pasture to crops (USDA NASS, 2013). In terms of row crops, cotton production in the early 1980s had dropped below 100,000 hectares (USDA NASS, 2013). As prices increased and management practices improved, the harvested area rapidly increased to over a million hectares by 1995 (USDA NASS, 2013). Even though cotton prices remained high and expected profitability appears to have continued to exceed that of other crops, the proportion of cropland in cotton did not increase beyond 40% (USDA NASS, 2013). Such historical examples suggest how switchgrass adoption will be limited by other factors aside from breaking even.

3.5.2 Environmental Implications

Despite limitations to projecting actual land conversion, approximating breakeven potential of switchgrass on different types of land provides a foundation on which to assess LUC implications. Row crops and hay production in the region often require a large degree of agricultural input. Producing switchgrass on these lands has the potential to greatly reduce impacts. Decreased fertilizer use on managed cropland can improve water quality (Sarkar et al., 2011). In terms of soil enrichment and carbon sequestration, switchgrass also holds potential for significant improvement over intensively farmed land in the region (Chamberlain et al., 2011). On the other hand, producing switchgrass on unmanaged land may not be as beneficial because fertilizer use could increase and have a smaller contribution to soil improvement (Chamberlain et al., 2011).

3.5.3 Policy Implications

In the context of environmental consequences of an emerging bioenergy crop, there are policy considerations that accompany breakeven results. Information regarding profit potential for converting land to switchgrass combined with estimates of environmental effects according to land type can aid policy makers in drafting measures that maximize the ecological benefit of developing a regional bioenergy industry. Incentivizing land conversion through carbon credit and penalizing fertilizer use is one example of managing switchgrass expansion (Chamberlain and Miller, 2012). Such mechanisms shift profitability towards converting intensively farmed land which support soil enhancement and diminish nitrate runoff.

Successful implementation of policy such as those that target environmental concerns and minimize costs for transitioning to switchgrass could drive production toward achieving 10% blending with gasoline as indicated in the breakeven results; however, there are regulatory and market constraints for moving beyond this percentage of ethanol. The U.S. Environmental Protection Agency addressed concerns of maximum ethanol blending with gasoline for use in all gasoline-powered vehicles under Federal regulations in announcing U.S. RFS production requirements for 2014 (US EPA, 2013a). The blendwall of 10% ethanol combined with gasoline, E10, could limit switchgrass-to-ethanol production because consumption of higher blends such as E85 is further constrained by market and infrastructure (US EPA, 2013a).

Other studies have suggested potential for co-firing switchgrass with coal as an alternative utilization strategy (Aravindhakshan et al., 2010; Dumortier, 2013; Qin et al., 2006). The southeastern states in the current study generate between 33% and 51% of their electrical power from coal, which has initiated regional economic and policy analyses of co-firing with biomass such as switchgrass (Bush et al., 2001; Chamberlain, 2011; EIA, 2011; English et al., 2007). Though Georgia and South Carolina do not have targets for using renewable energy for electricity generation as part of the Renewable Portfolio Standard (RPS), North Carolina has enacted RPS policy to achieve 12.5% of electricity from renewable sources by 2021 (North Carolina General Assembly, 2007). Such directives and bioenergy options are also expected to influence switchgrass price and corresponding production potential with dual outlets for biomass (Dumortier, 2013).

The breakeven analysis considers switchgrass price as an independent variable from the perspective of potential producers; however, viewing switchgrass price in terms of two sources of demand suggests significant price increases to accommodate both industries. Due to limited sources of other cellulosic material such as corn stover in these states, switchgrass along with other biomass would not be able to meet both RFS and RPS goals (Dumortier, 2013).

In a study that compared switchgrass for ethanol versus co-firing with coal for southeastern states, results showed economic advantages for conversion to ethanol while co-firing suggested greater benefit for greenhouse gas reduction (Chamberlain, 2011). Aravindhakshan et al. (2010) encountered similar findings for the U.S. southern plains, where switchgrass production costs of $43.90 Mg^{-1} was nearly double the regional cost for coal when accounting for energy content (Aravindhakshan et al., 2010). In terms of policy necessary to direct switchgrass to co-firing, a carbon tax of $7 Mg^{-1} CO_2 was estimated. On the other hand, applying environmental outcomes of each utilization strategy to transportation energy, biomass such as switchgrass used for bioelectricity outperforms conversion and use of ethanol for transport in terms of life cycle greenhouse gas emissions (Campbell et al., 2009).

Using the perspective of the producer, this breakeven analysis by land type focuses on insight for land use change effects as part of the total life cycle impact for either use of switchgrass. Policy may help steer production toward lands that stand to gain the most environmentally; however, a combination of economic and life cycle investigations for downstream processes brings a broader context to policy for achieving optimal environmental benefit in balance with switchgrass profitability.

3.6 Conclusion

This paper elucidates sources of uncertainty in projecting the quantity and type of land that may be more profitable if switchgrass were a viable alternative. The approach uses switchgrass price as an independent factor such that variability of expected revenue at different prices suggests production capacity on lands with different agricultural intensities. Breakeven findings show significant capacity for managed cropland to grow switchgrass at prices that are comparable to the market price for hay (USDA NASS, 2013). Though marginal land and pastureland can contribute breakeven area at lower prices they also have less potential for environmental improvement. Overshadowing breakeven estimates are the behavioral factors and policy implications that may strongly affect diffusion and shift maximum potential adoption for switchgrass in the Southeast.

4 PROJECTING SWITCHGRASS ADOPTION TO DETERMINE REGIONAL AGGREGATE IMPACTS OF A PROPOSED SWITCHGRASS-TO-ETHANOL INDUSTRY IN THE SOUTHEASTERN U.S.

Chapters 2 and 3 provide a foundation for implementing diffusion of innovation methods for the switchgrass-to-ethanol system. To assess the maximum level adoption, breakeven results are analyzed in terms of historic market penetration of crop production according to profitability. The well-established Bass diffusion model is applied to give a rate of adoption context. Results of these adoption analyses are combined with results from previous LCA studies to give an overall picture of sustainability for the system.

This chapter is intended for submission as a journal article for the *Journal of Environmental Management*.

4.1 Abstract

A switchgrass-to-ethanol case study for the southeastern U.S. is used to demonstrate methods for gauging aggregate environmental effects of an emerging energy technology. The amount and type of land converted to switchgrass provide estimates for the total land use change (LUC) effects, biomass production, and overall impact of the regional switchgrass-to-ethanol system as measured by greenhouse gas (GHG) emissions, net fossil energy, and nitrate loss. This comprehensive appraisal is achieved by first assessing maximum switchgrass adoption within previously determined breakeven areas for farm-gate prices of \$50, \$100, and \$150 Mg^{-1}. Regression analysis shows that hectares of pasture and hay lands are historically not associated with crop production profit, which suggests

minimal switchgrass adoption. In contrast, marginal cropland and land in row crops have historically responded to changes in profit from row crops. Determining the long-term maximum adoption of switchgrass on marginal cropland and land in row crops requires judgment based on switchgrass performance and farmer willingness to devote land to perennial switchgrass production for increased profit over traditional crops. The maximum proportion of adoption for switchgrass breakeven area on marginal land and land in row crops is approximated at 0.75 for both land categories. Next, the Bass diffusion model is used to approximate the rate of adoption using previous applications of agricultural adoption. Finally, previously determined life cycle assessments of the system are aggregated according to adoption estimates at each price. At \$100 Mg^{-1}, switchgrass is projected to be grown on about 0.8 million hectares of land in row crops and 0.5 million hectares of marginal cropland, land in hay and pastureland, which translate to about 5.4 billion liters of annual ethanol production. This amount of ethanol is equivalent to about 9% of gasoline consumed annually in the region. Because LUC benefits are enhanced by primarily converting row crops switchgrass, GHG emissions are reduced by about 2 billion kg CO_2e yr^{-1} from land conversion. Displacing tailpipe emissions from gasoline can contribute about six times as much GHG. According to historic agricultural adoption trends, about 20 years are needed to approach the required level of switchgrass production. At the higher price of \$150 Mg^{-1}, switchgrass adoption is more rapid and would require 11 years to reach roughly the same level of production.

4.2 Introduction

The net environmental benefits of an emerging biofuel industry depend on life cycle impacts at each stage of the well-to-wheel process as well as the extent that sources of bioenergy are integrated into regional agricultural systems. The amount of biomass produced determines industry size and allows for life cycle assessments (LCA) made on a per-unit basis to be translated into aggregate environmental outcomes for the region. Estimates of production capacity have been calculated according to the degree that growing dedicated biomass is more profitable than existing land uses (US DOE, 2011); however, the time frame and degree of participation in an emerging biofuel industry depend on additional factors that affect decisions to convert land (Qualls et al., 2012).

This paper applies diffusion of innovation concepts to a proposed switchgrass-to-ethanol system for the southeastern U.S. Probable switchgrass adoption trends are used to approximate the overall regional impacts of the system. Projections of land conversion to switchgrass are assessed for four different land types in order to aggregate estimates of land use change (LUC) effects. The results are subsequently viewed in terms of impacts associated with biomass transport and conversion to ethanol. Informed scenarios of switchgrass adoption coupled with LCA results provide aggregate impact estimates of fossil fuel use, greenhouse gas (GHG) emissions, and water quality.

The assessment of three impacts is managed in three separate steps. First, the maximum amount of land converted is estimated in the context of the previous breakeven study. Next, the time frame for switchgrass adoption is evaluated according to historic adoption trends in agriculture. Third, LCA results are applied according to maximum adoption estimates in order to aggregate impacts. The assessment results are considered in the context of aggregate impacts over time and timelines for national ethanol production goals set by public policy.

Diffusion of innovation research examines the propensity for an innovation to be adopted by a population. In this case, the Bass diffusion model is applied to switchgrass adoption on different types of land. The Bass model is an established method within marketing and management science used to describe adoption of new durable products (Peres et al., 2010). Applying this modeling technique to the diffusion of agricultural technologies provides parameter estimates to project switchgrass adoption.

The Bass diffusion model indicates adoption over time. The extent that each category of land will be converted to switchgrass requires additional analysis. The four land types considered in this study have been previously assessed in terms of the land area that is expected to break even by producing switchgrass (Sharp and Miller, In Press 2013). The degree that the breakeven areas may actually be converted to switchgrass will be affected by broader economic and behavioral factors that vary according to land category. With data available for estimating annual profits per hectare, potential financial gain is used as an indicator of farmer willingness to adopt switchgrass for increased profit. Regression analysis of previous farmer behavior in response to crop profitability is used to measure the potential to grow switchgrass on each type of land.

4.3 Background

The national U.S. Renewable Fuel Standard (RFS) mandates annual production of 16 billion gallons of cellulosic ethanol by 2022. To achieve this target, areas such as the southeast are expected to contribute perennial grasses for ethanol production (USDA, 2010). The following analysis projects the extent of environmental effects as they are confined by the three-state region of Georgia, North Carolina, and South Carolina.

Ethanol from cellulosic material is expected to realize environmental advantages over the corn grain ethanol system (Hsu et al., 2010). Perennial crops such as switchgrass are also expected to grow on degraded soils to further reduce food-fuel production conflict and diminish GHG effects due to land use change (Searchinger et al., 2008). Furthermore, switchgrass grows well with less agricultural input compared with traditional crops which translate to additional environmental advantages (McLaughlin and Adams Kszos, 2005).

Although full commercial-scale production of ethanol from cellulosic material has yet to be realized in practice, technologies for the conversion process are also anticipated to improve environmental effects over the corn grain system (Hsu et al., 2010; Spatari et al., 2010; US EPA, 2013a). The life cycle benefits of a switchgrass-based ethanol system hold promise for outperforming first-generation methods of biofuel production, but total net effects depend on the amount of intensively farmed land that is converted to switchgrass.

Profitability of growing dedicated perennial grasses for energy has been extensively studied (National Research Council, 2011; Boyer et al., 2013; Perlack and Stokes, 2011; Mooney et al., 2009; Miranowski and Rosburg, 2010; Landers et al., 2012). My study is based on the analysis of the number of hectares that are projected to break even for the different types of land in the region across a range of switchgrass prices (Sharp and Miller, in Press 2013). The potential for switchgrass production is limited to pastureland, marginal cropland, land in hay, and rotated annuals dominated by corn, cotton, soybeans and wheat. Assuming profitability is a fundamental driver of adopting switchgrass, capacity is dictated by those hectares that stand to increase existing profits by growing switchgrass.

Previous breakeven results frame the assessment for switchgrass adoption with respect to land type. The interest of the current study is to approximate the maximum proportions of each breakeven area that is expected to be converted to switchgrass. To approximate total maximum adoption, previous breakeven results are multiplied by respective proportions (Equation 1). The total number of hectares of switchgrass adoption for the region, SG_{tot} is

$$SG_{tot} = BE_{row} \times m_{row} + BE_{past} \times m_{past} + BE_{mar} \times m_{mar} + BE_{hay} \times m_{hay}, \qquad (1)$$

where *BE*-variables are breakeven areas for respective land types from prior work and *m*-variables are maximum proportions to be approximated.

Proposed switchgrass prices of \$50, \$100, and \$150 Mg^{-1} are considered. Table 4.1 shows estimated breakeven land areas under the reference case at the above prices (Sharp and Miller, In Press 2013).

Table 4.1 Breakeven Capacity by Switchgrass Price

SG Price ($/Mg)	Total Hectares (10^3) of Land that Breaks Even Pasture	Marginal	Hay	Row Crops	Total
50	790	224	92	58	1,164
100	1,664	404	453	1,118	3,639
150	1,849	440	650	2,086	5,025

(Values are from Chapter 3 reference case scenario)

4.4 Extent of Land Conversion to Switchgrass

Substantial differences in the maximum proportion of breakeven area are anticipated for each land category. For example, broader economic influences are likely to affect the capacity at which pasture is turned into switchgrass for profit versus displacing traditional row crops for profit. Pastureland operates under influences from the livestock industry, and greater initiative to exchange land designated for grazing is required to be adapted for crop production (Dicks et al., 2009). Active cropland is operated under shifts toward cropping strategies that promote long-term profits from crop production. The key interest in this section is to determine the respective *m* estimates from Equation 1 for each land type.

Linear regression models are used to help determine possible values for *m*, which were conducted using R statistical software (R Development Core Team, 2010). Analyses for potential conversion of pasture, hay, and marginal lands are managed according to overall profitability of row crops. In a separate section, the propensity for land shifts in row crops is considered according to relative profits and changes in land area for corn, cotton, and soybeans.

4.4.1 Conversion of Land Not Used for Row Crops

Several sources suggest that switchgrass is expected to be grown on pastureland and marginal cropland (Landers et al., 2012; Mooney et al., 2008; Schmer et al., 2008; Walsh et al., 2003). The U.S. Department of Energy Billion-Ton Update suggests minimal conversion of U.S. pastureland for biomass prices under \$55 Mg^{-1}; however, at \$66 Mg^{-1}, pastureland is anticipated to surpass cropland in producing grasses for bioenergy by 2022 (US DOE, 2011). By 2030, pastureland converted to grass is projected to be twice that of cropland at this higher price(US DOE, 2011).

On the other hand, such optimistic scenarios are expected to have important impacts on hay and livestock markets (Acheampong et al., 2011; Dicks et al., 2009). Increased beef prices due to land constraints may hinder enthusiasm for transitioning pasture to switchgrass despite initial indications of increasing profit per hectare. Of surveyed farmers, those managing livestock indicate they are less willing to convert land to switchgrass (Qualls et al., 2012). Market resistance coupled with decreased willingness to convert pasture suggests that there may be substantial limitations to switchgrass production on pastureland.

The market constraints for switchgrass penetration on pastureland are likely to apply to land in hay because each are associated with the livestock industry. For my study, the degree of inelasticity for hay is expected to be somewhat lower than that of pastureland because surveys of southeastern farmers show that access to hay equipment has a positive relationship with willingness to grow switchgrass since the same farm equipment may be used for switchgrass management (Jensen et al., 2007; Qualls et al., 2012). Furthermore, data show that hay production in the region typically requires significantly more fertilizer than with switchgrass (Sharp and Miller, In Press 2013). With the potential for increases in fertilizer costs, converting hay land may be a more appealing option than converting permanent pastureland to switchgrass.

Marginal cropland is difficult to define consistently across regions (Gopalakrishnan et al., 2008; Mooney et al., 2008). The extent to which farmers are willing to manage switchgrass production where other crops have performed poorly also compounds the challenge to approximating the extent that marginal land is converted to switchgrass. Many switchgrass test plots have been planted in lower quality soils with the expectation that switchgrass is targeted for these conditions (Wullschleger et al., 2010). Marginal cropland also has minimal competition for other uses and has seen greater fluctuations over time than areas of pastureland and hay. This trait indicates that marginal cropland may be more amenable to switchgrass.

In order to assess the potential conversion of hay, pasture, and marginal land to switchgrass, historic land use change is considered relative to profits from major annual crops for the region. Substantial increases in expected profits by converting pasture, hay, or marginal land to traditional crops can indicate the potential to convert these lands to switchgrass for greater income.

Linear regression analyses are performed for each of the three land types separately using census of agriculture data from 1978 to 2007. Total land area in hay, pasture, and marginal cropland are available every five years for Georgia, North

Carolina, and South Carolina. Changes in land area between each census collection for each state are compared to crop profitability during that time. The expectation is that changes in crop profits can be used to predict changes in land area. A relationship between crop profit and land changes signals propensity for pasture, marginal cropland, and land in hay to convert to switchgrass to for potential higher profit per hectare.

Profit per hectare from row crops are estimated annually from USDA survey data from the National Agricultural Statistics Service (NASS) and the USDA Economic Research Service (ERS). Each year, county-level and state-level data are collected for crop yield and made available by the NASS. For each commodity used in the analysis, state-level prices are estimated by a market year price according to appropriate metrics – bushels for corn, soybeans, and wheat, and pounds for cotton and peanuts (USDA NASS, 2013). Variable costs of each crop are estimated from annual ERS regional data (USDA ERS, 2013a). Variable costs for this study include total cash expenses less general farm overhead, insurance, and hired labor. Estimated yearly profits are then calculated for each by multiplying yields by prices and subtracting the variable cost estimate. Profit estimates are based on state-level yields, state prices, and regional costs. Since yield is likely the most variable factor, the profit approximation is assumed to be appropriate at the state level for each crop. (County-level profit approximations are found by using county-level yields, state prices, and region costs). For the following regression analyses, state level profit per hectare approximations are used.

To establish a general gauge of overall profitability, each crop profit estimate is weighted according to the amount of harvested area for each state for each year. Weighted averages provide a state-level value for annual profits for row crops per hectare from 1979 to 2006. A short-term trend in profits is captured by averaging the three years prior to each census collection. By averaging over this time span, the fluctuation in average annual profits are smoothed. Also, the smoothing process is likely suggestive of how farmers respond to more sustained changes in profits as opposed to annual profit volatility. Each state has a data point for the three-year average of estimated profit from row crops for each census collection.

The analyses use the profit data points for each state and each census collection and compares them to the respective percent change in land area for each land type in each state. Figure 4.1 shows approximate average profits from row crops versus percent changes in pastureland. Eighteen total data points are produced, where six data points for each state is color coded to illustrate variation between states for the six censuses. Data for Georgia, North Carolina, and South Carolina are shown in blue, red, and black, respectively.

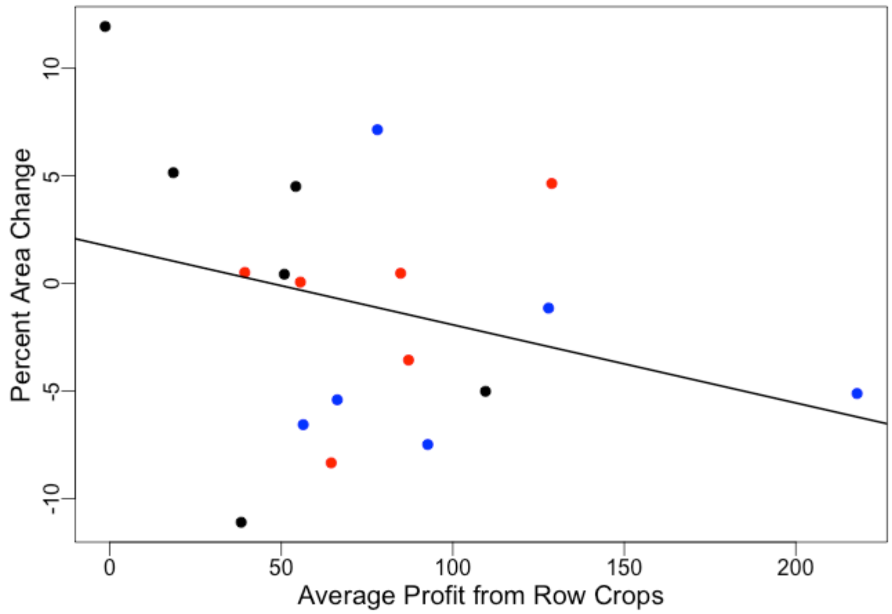


Figure 4.1 Percent Change in Pasture Area between 5-Year Intervals of Censuses from 1978 to 2007 for Georgia (blue), North Carolina (red), and South Carolina (black) Versus 3-Year Average Profit from Row Crops ($R^2 = 0.087$)

The regression plot for pastureland versus average profit from row crops show a weak relationship. For the three years prior to the 1997 census, profits from row crops in Georgia were much higher. There was about a 5% drop in pastureland for that census. Otherwise the scatter plot shows little evidence that high crop profits reduce pastureland area. The regression line shows the expected trend, but it is largely attributed to the high leverage associated with the 1997 data point for Georgia. The p-value for this linear model is 0.23 which is greater than an alpha level of 0.05. For pasture, there is not a significant relationship between crop profits and land conversion.

Using the same three-year averages for profits from row crops, a similar analysis is performed for percent change in marginal cropland between census collections over the same period. Figure 4.2 shows a more convincing pattern than for changes in pastureland area; however, there is a set of outliers for each state. For the 1987 census, the number of idle hectares for all three states jumped dramatically. The change is likely due to a combination of factors that include weather conditions for planting and shifts in programs for conservation and acreage reduction (USDA NASS, 1987). When leaving the outliers in the model, a p-value of 0.12 is found. Without the three data points, p = 0.009. Unlike pastureland, marginal cropland decreases when crop profits increase according to a statistically significant level when adjusting for the data collected in 1987. The result suggests that marginal cropland may convert to crops for increased profit. The relationship is expected to also be true for increased profit with switchgrass on marginal land.

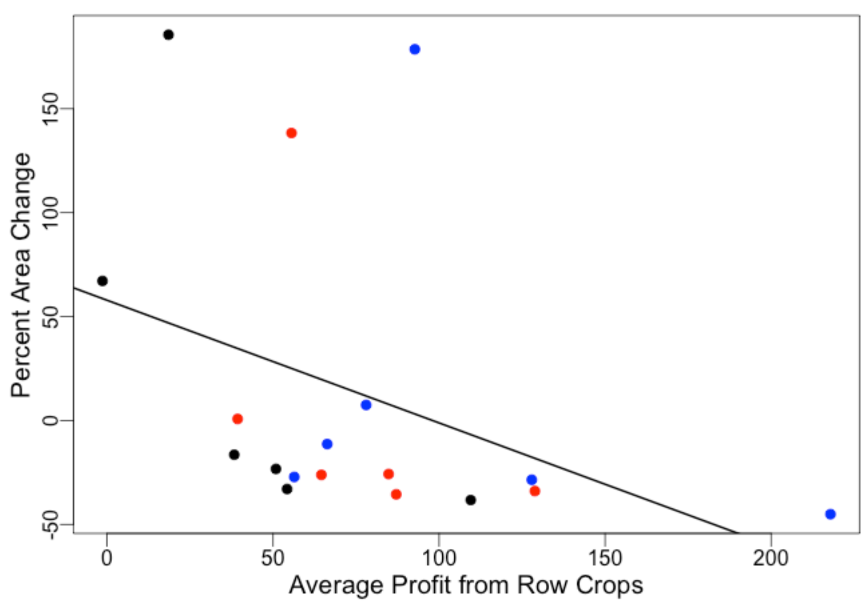


Figure 4.2 Percent Change in Marginal Cropland Area between 5-Year Intervals of Censuses from 1978 to 2007 for Georgia (blue), North Carolina (red), and South Carolina (black) Versus 3-Year Average Profit from Row Crops (R^2 = 0.15, with 1987 data removed R^2 = 0.42)

The regression method is carried out similarly for land in hay. The same state-level average profit from row crops are compared to percent change in land area for hay in each state between agricultural census collections. Figure 4.3 shows a scatter plot with the fitted line. There is not a significant relationship between profit from row crops and change in hay area. A linear model that includes hay prices during the same time periods also did not produce a significant relationship. No significant relationship is apparent between profit from row crops and changes in land area for hay production. Along with pastureland, land in hay results suggests minimal response to land conversion relative to crop profitability.

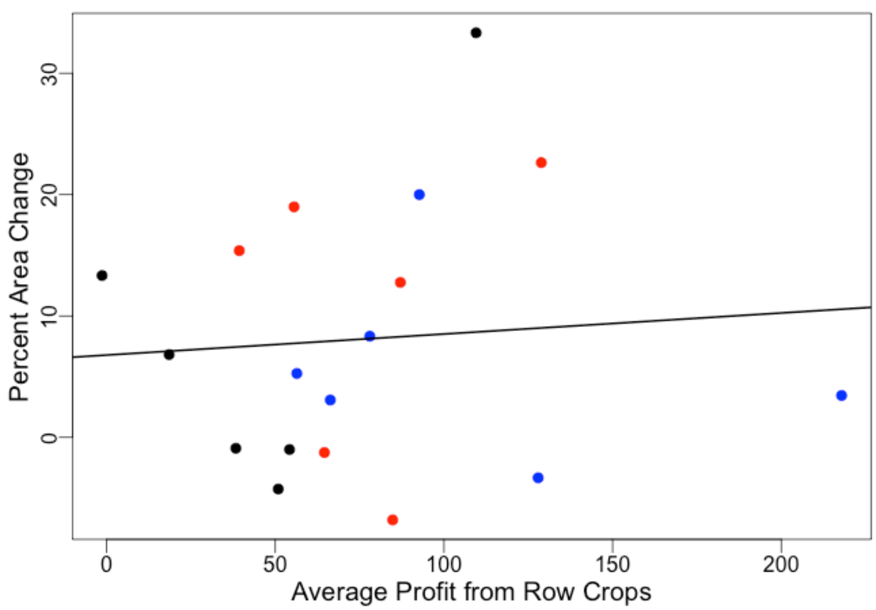


Figure 4.3 Percentage Change in Land in Hay between Five-Year Intervals of Census Data from 1978 to 2007 for Georgia (blue), North Carolina (red), and South Carolina (black) Versus Three-Year Average Profit from Row Crops (R^2 = 0.006)

Data from census of agriculture from 1978 to 2007 indicate that farmers are not willing to grow row crops on hay and pastureland despite potential for increased profit. On the other hand, publications suggest that switchgrass is expected to penetrate these types of land due to its agricultural advantages over traditional crops. Less effort managing switchgrass along with potentially more stable pricing may increase switchgrass utility over row crops used in the regression analysis (Wright and Turhollow, 2010).

Gauging land elasticity according crop profit is inherently a non-linear relationship as the supply of land is constrained (Barr et al., 2011). The linear regression analysis demonstrates relationships between profitability and changes in land area; however, the maxim degree of conversion over the long term must also be informed by subjective evaluation of the extent that the agricultural system in the southeast can tolerate displacement existing land uses with switchgrass.

Considering published expectations in light of the regression results, the assumption is that there will be some switchgrass penetration into pastureland and hay production areas, but it will be minimal. The estimated m-value for pastureland is lowest at 0.10 because survey results show that farmers with livestock are less interested in switchgrass compared to all survey respondents (Jensen et al., 2007; Qualls et al., 2012). A value for m of 0.15 is appropriate for land in hay as a compromise between the lack of a relationship with profit from row crops and the more favorable response to converting land in hay indicated by surveys (Jensen et al., 2007; Qualls et al., 2012).

Conversion of marginal croplands to switchgrass is likely more positive because these lands have minimal competition for other uses, and a significant relationship between crop profits and marginal cropland changes exists. On the other hand, it is challenging to determine switchgrass conversion in terms of the USDA definitions applied to marginal croplands. As part of crop rotation strategies and crop performance, marginal croplands are idled for various agricultural reasons (USDA NASS, 2007). Furthermore, a nation-wide study for the U.S. showed that the substantial jump in field crop prices from 2006 to 2009 precipitated a 64% increase in profitability, but planted area increased by only about 2%, which was largely in the central plains (Swinton et al., 2011). The results of the national study show minimal conversion of non-crop land to active crop production in the southeast implying that marginal land offers limited production value for biofuel crops (Swinton et al., 2011). Achieving switchgrass adoption at full breakeven capacity of marginal cropland is doubtful when considering data definitions of marginal land and its potential other uses when remaining inactive in terms of crop production despite exceptional profitability.

To compromise between optimism indicated in publications along with the regression results discussed above, an *m*-value of 0.75 is assessed for marginal cropland. The degree that farmers are willing to convert marginal cropland that breaks even with switchgrass over the long term will be determined by switchgrass performance in conjunction with cropping strategies. Suggested relative advantages of switchgrass by land type are reflected in maximum adoption proportions of breakeven area shown in Table 4.2.

Table 4.2 Assigned Maximum Proportion of Breakeven Area Converted to Switchgrass by Land Type

Land Type	Assigned Maximum of Breakeven
Pasture (m_{past})	0.10
Marginal (m_{mar})	0.75
Hay (m_{hay})	0.15
Row Crops (m_{row})	0.75

4.4.2 Conversion of Land in Row Crops

A similar regression method is used for planted area of individual crops. Percent change in land planted in corn, cotton, and soybeans are assessed individually relative to their respective profitability compared to other row crops. The following analyses test for a relationship between changes in area planted of a crop as determined by increased profit potential. The expectation is that if farmers shift land in row crops to those crops that are most profitable, then they also will convert land in row crops to switchgrass for increased profit.

More detailed and more frequent data are available for crops compared to that for pastureland, marginal land, and land in hay. For example, annual planted area for each crop are collected at the county and state levels as opposed to only during census years. To maintain consistency with the analysis for land not in active row crops, only changes in land area between census years are used for the regression analysis.

Approximations for crop profit per hectare is conducted at the state level as with the regression analysis for land not in row crops. In this case, a three-year average of profit for the crop of interest is compared to an overall three-year average of the other major row crops as weighted by their respective planted areas. Since, a single crop is examined for land in row crops, profitability per hectare for the single crop is compared to the weighted average of all the other crops, as opposed to a weighted average for all crops as used for analyzing changes in non row-crop lands. For years and states where a crop is more profitable than the average of other crops, it has a positive value. If on average it is less profitable, then it has a negative value.

First, corn is evaluated between 1978 and 2007. Weighted average profits from cotton, peanuts, soybeans, and wheat for each state are subtracted from estimated corn profits to represent relative corn profits. For the three years prior to each census collection, the annual relative corn profits are averaged. Figure 4.4 shows the percent change in corn planted area between each census collection year according to relative corn profit for each state. Data for Georgia, North Carolina, and South Carolina are indicated by red, blue, and black data points, respectively. The correlation between the percent change for area in corn and relative profit is statistically significant at p=0.0054, where increase in relative profit suggests an increase in planted area for corn.

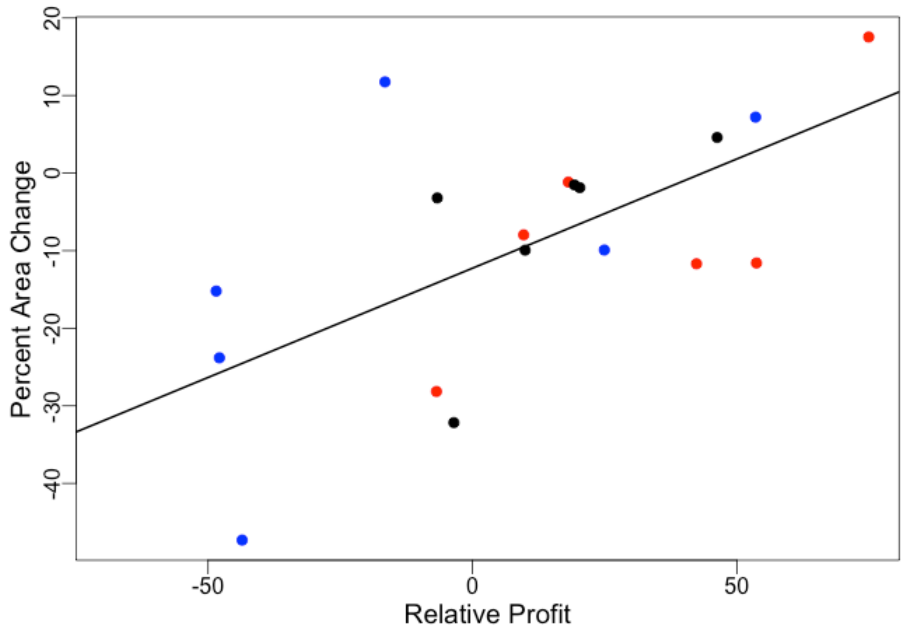


Figure 4.4 Percentage Change in Land in Corn between Five-Year Intervals of Census Data from 1978 to 2007 for Georgia (blue), North Carolina (red), and South Carolina (black) Versus Three-Year Average of Relative Corn Profit (R^2 = 0.39)

The same method is applied to soybeans. Relative profit is calculated by comparing soybean profit per hectare estimates with the weighted average estimates for corn, cotton, peanuts, and wheat. The percent change in land area planted in soybeans between each census is predicted by a three-year average of relative soybean profit prior to the census year. A relationship is also demonstrated with soybeans, where p=0.065. One reason for a weaker correlation compared to the corn analysis is that soybean production in Georgia was less stable. In 2007, soybean land area doubled for Georgia compared to the 2002 census, which created an outlier as shown in Figure 4.5. With data point removed, the fitted model has a stronger relationship where p=0.025.

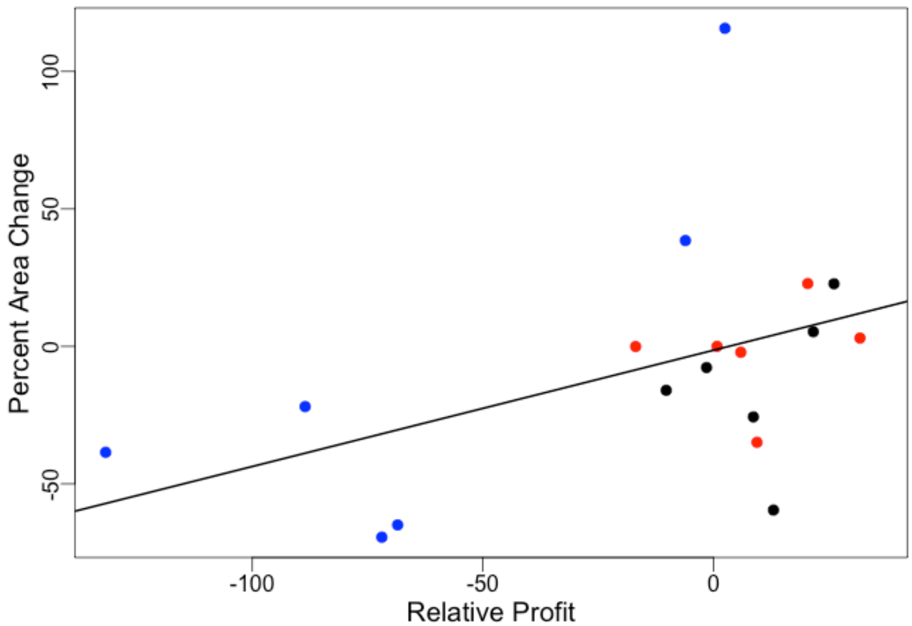


Figure 4.5 Percentage Change in Land in Soybean between Five-Year Intervals of Census Data from 1978 to 2007 for Georgia (blue), North Carolina (red), and South Carolina (black) Versus Three-Year Average of Relative Soybean Profit ($R^2 = 0.20$)

Finally, relative cotton profit is used to predict percent change in cotton planted area. Using the same methods as for corn and soybeans, a fitted linear model shows a significant relationship where $p = 0.013$. The fitted model for cotton is shown in Figure 4.6.

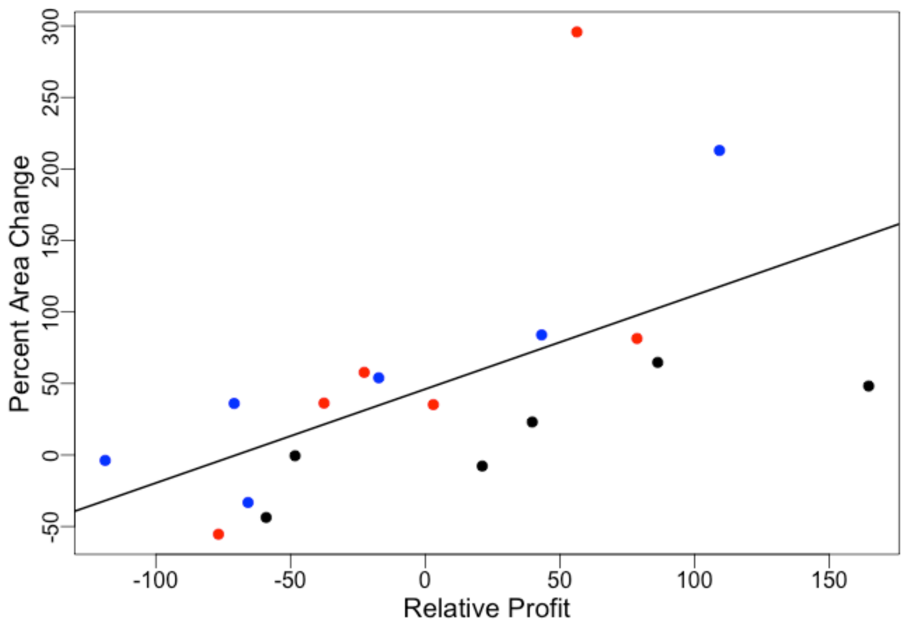


Figure 4.6 Percentage Change in Land in Cotton between Five-Year Intervals of Census Data from 1978 to 2007 for Georgia (blue), North Carolina (red), and South Carolina (black) Versus Three-Year Average of Relative Soybean Profit (R^2 = 0.33)

The three crop examples demonstrate that farmers use land in row crops for producing crops that stand to generate profit. Even though switchgrass is a perennial crop, the expectation is that switchgrass will be treated in a similar fashion. If switchgrass breaks even over other crops, then farmers appear willing to adapt land in row crops accordingly. The extent at which farmers will adopt switchgrass within the breakeven capacity over the long term is likely to be substantial given historical response to profit potential.

Because switchgrass is a perennial crop, farmers must commit land for a longer term. Setting land aside for an extended period can potentially provide a more steady production and profit compared to traditional row crops. Committing land for an extended period can also create a risk of foregoing higher profits if row crop prices surge. A risk evaluation suggests that farmers may also stick with familiar crops over the long term especially when considering the costs of reverting back to traditional crops (Song et al., 2011).

Furthermore, when cotton prices dropped in 2001 compared to other crops, farmers continued growing cotton when they may have increased profit per hectare by selecting corn or soybeans (USDA NASS, 2013). This phenomenon may indicate reluctance to divert cotton land despite the potential for greater profit with corn or soybeans. There remains a "king cotton" sentiment in the southeast that suggests possible resistance to conversion to switchgrass as well (Frederick, 2013). Extenuating factors may interfere with farmers acceptance of switchgrass to reach full breakeven capacity of production.

To accommodate the significant relationship in shifts to crop area relative to respective crop profit and the broader economic and behavioral factors, a maximum proportion of breakeven switchgrass adoption of 0.75 is assigned to land in row crops. Seventy-five percent of breakeven capacity also matches that estimated for marginal cropland.

Using the values in Tables 4.1 and 4.2 for Equation 1 provide an overall estimate for the maximum adoption of switchgrass in the region according to the different switchgrass prices. The maximum number of hectares expected to be converted are shown in Figure 4.7. The results are used to approximate annual biomass production and to aggregate annual regional impacts according to LCA results as summarized in section 4.5. Aggregating impacts using maximum adoption estimates does not account for the period of time that is necessary to realize such outcomes. Further analysis is necessary to gauge potential immediate environmental effects of switchgrass, and to consider the price scenarios in the context of policy objectives.

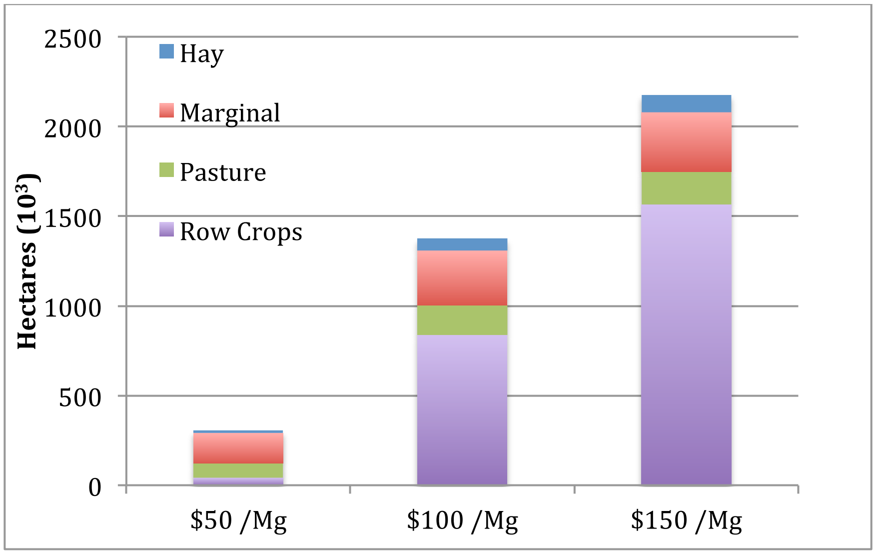


Figure 4.7 Maximum Number of Hectares Expected to Be Converted to Switchgrass according to Land Category and Price Scenario

4.5 Rate of Cumulative Adoption

Several key examples of diffusion have been studied within the U.S. agriculture sector that provide insight into probable behavior that may be applied to switchgrass adoption. Analysis of expansion of hybrid corn serves as one case study (Griliches, 1957). More recently, data for the adoption of genetically engineered (GE) crops have been collected by the US Department of Agriculture (USDA ERS, 2013b). The regional changes of hectares of cotton over the last 30 years are used as an example. Examining the diffusion of these cropping strategies provides useful information for estimating the time frame of prospective agricultural innovations that stand to increase farmer profits. By applying the Bass model to hybrid corn adoption and reemergence of cotton, parameter estimates can indicate the rate of cumulative adoption.

In diffusion of innovation terms, the rate of adoption is influenced by the relative advantage, trialability, compatibility, complexity, observability of the new technology (Rogers, 1995). The diffusion of new crops and cropping strategies is likely to be relatively similar with switchgrass for compatibility, complexity, and observability. For compatibility, the expectation is that farmers are able to incorporate switchgrass as part of their cropping strategy similar to historic integration of hybrid corn, GE crops, and cotton. Though switchgrass is a perennial, it is straightforward to farm, which also minimizes complexity of adoption (Wright and Turhollow, 2010). Observability indicates the level of awareness of an innovation and suggests the rate it spreads through a population (Rogers, 1995). In this case, landscape producing switchgrass may have an advantage over less apparent changes to agricultural land from hybrids or genetically engineered crops because switchgrass is a more visible alteration from the more subtle changes from traditional crop seeds.

Trialability captures the ease at which a new technology can be tested or adopted without requiring commitment. A possible difference in trialability between switchgrass and many crops is that switchgrass is a perennial crop that requires comparatively higher transaction costs. The difference is assumed to be negligible in light of switchgrass's potentially higher profile combined with anticipated support such as with the Biomass Crop Assistance Program (BCAP)

(Griffith et al., 2009). The benefit of increased observability and potential assistance to switchgrass adoption are assumed to offset challenges posed by trialability compared to traditional annual crops. The primary factor to take into account is the relative advantage of growing switchgrass compared to existing cropping strategies.

A well-documented theme to many agricultural diffusion examples is that farmers expect to gain financially by investing in the innovation (Daberkow and McBride, 2003; Fernandez-Cornejo, 2007; Griliches, 1957; McBride and El-Osta, 2002; Rogers, 1995). The balance between risk and gain is also visible in the current rate of adoption of different types of precision farming technologies. More affordable precision farming technologies with proven efficiencies are more readily adopted while more expensive options fail to achieve significant market penetration (Schimmelpfennig, 2011). The above agricultural diffusion example lends credence to using an adoption evaluation in context of breaking even.

Innovations such as GE crops and hybrid corn have relatively low financial barriers and offer apparent relative advantages. They tend to spread at a reasonably predictable progression. The level of utility varies for adopting GE crops according to location and characteristics of pests and management practices; however, the amount of time to reach full saturation is fairly stable (McBride and El-Osta, 2002; USDA ERS, 2013b). The consistent adoption behavior is represented by diffusion of different GE crops.

There are five basic types of genetically engineered crops. Corn, cotton, and soybeans each have an herbicide-tolerant variety. Corn and cotton also have insect-resistant varieties containing a gene from a soil bacterium, *Bacillus thuringiensis*

(BT). Although each GE crop has an associative utility depending on the degree of challenges that the GE variety overcomes, the market levels of each appear to stabilize at roughly the same time after simultaneous introduction in 1996. Figure 4.8 shows the 17 year history and the level of market penetration achieved for 2013 (USDA ERS, 2013b).

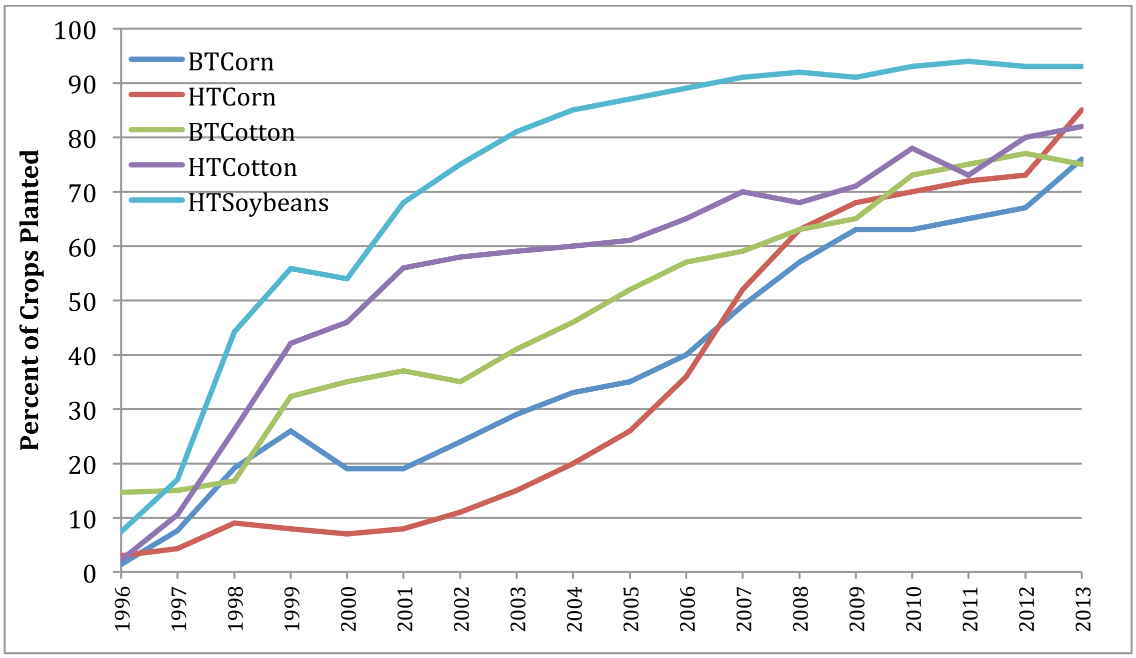


Figure 4.8 Adoption of Different Types of Genetically Engineered Crops

Hybrid corn adoption in the U.S. is a more straightforward representation of adoption compared to the various forms of GE crops. Cumulative hybrid corn adoption also reached near-saturation levels in a similar period of about 20 years. The Bass diffusion model is shown in Equation 2 as representing cumulative adoption over time:

$$F(t) = m\left[\frac{1-e^{-(p+q)t}}{1+\frac{p}{q}e^{-(p+q)t}}\right] \tag{2}$$

The Bass model describes diffusion according to an innovation parameter *p* and an imitation parameter *q*. In a meta-analysis of 213 products the innovation parameter ranged between 0.00021 and 0.033 with an average of 0.03 (Sultan et al., 1990). The relative size of *p* determines the initial rate of adoption. The imitation parameter from the meta-analysis ranged between 0.20 and 1.67 with an average of 0.38 (Sultan et al., 1990). This parameter is often used to describe the social contagion effect (Meade and Islam, 2006; Peres et al., 2010). The maximum proportion of the market that adopts is represented by *m*.

The Bass model is fit to hybrid corn data where values of *p* and *q* are estimated as 0.012 and 0.32, respectively using non-linear least squares approximation. The maximum adoption proportion is estimated at 0.91. The values for *p* and *q* are lower than the averages found from Sultan et al (1990) which suggests that hybrid corn planting across the U.S diffused slower than the durable products used in the meta-analysis.

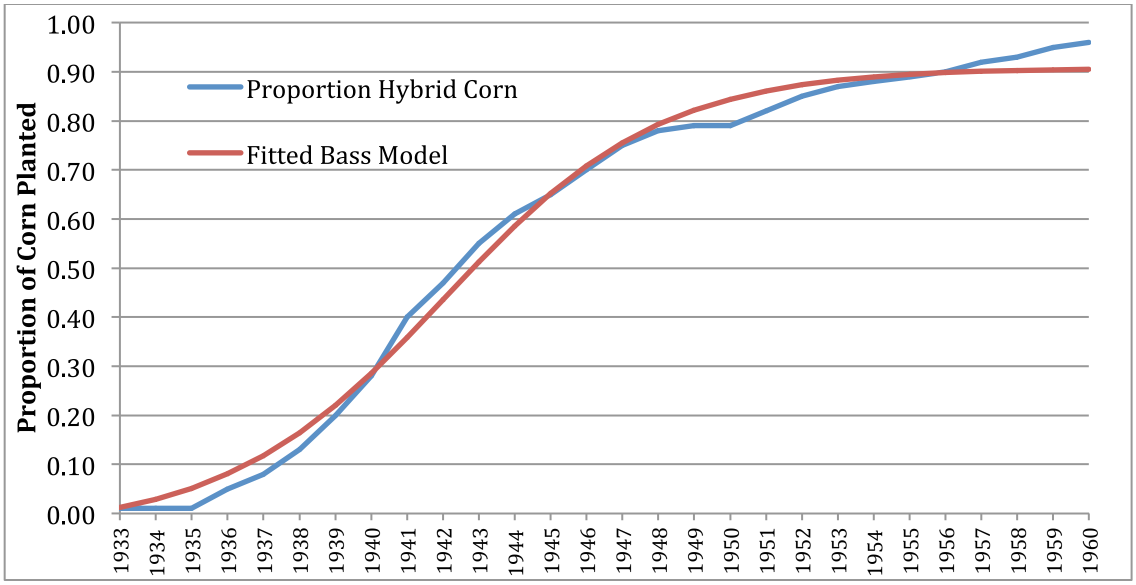


Figure 4.9 Hybrid Corn Adoption with Bass Model Fit

Another concern for applying the diffusion assessments above to switchgrass is that these innovations only entail changing management practices. Adopting switchgrass implies displacement of existing land uses. In order to address this difference, the recent reemergence of cotton is also examined as an analogue for prospective switchgrass adoption.

Figure 4.10 shows cotton production from 1980 until 2001. In 1983, a boll weevil eradication effort began in the southeast (Smith, 1998). With the diminished threat of boll weevil devastating cotton crops, the area of cotton harvests began to increase after more than a decade of minimal cotton production. Again, fitting a the Bass model to cotton production data for the 18 year interval between 1983 and 2001, q and p are estimated as 0.011 and 0.30, which are similar to estimates for the hybrid corn application. The displacement of other land uses for cotton appears to have weak resistance effect. The expectation is that switchgrass will have a similar diffusion pattern as hybrid corn and this era in cotton production in the region; consequently, values of 0.01 and 0.30 are applied to switchgrass diffusion.

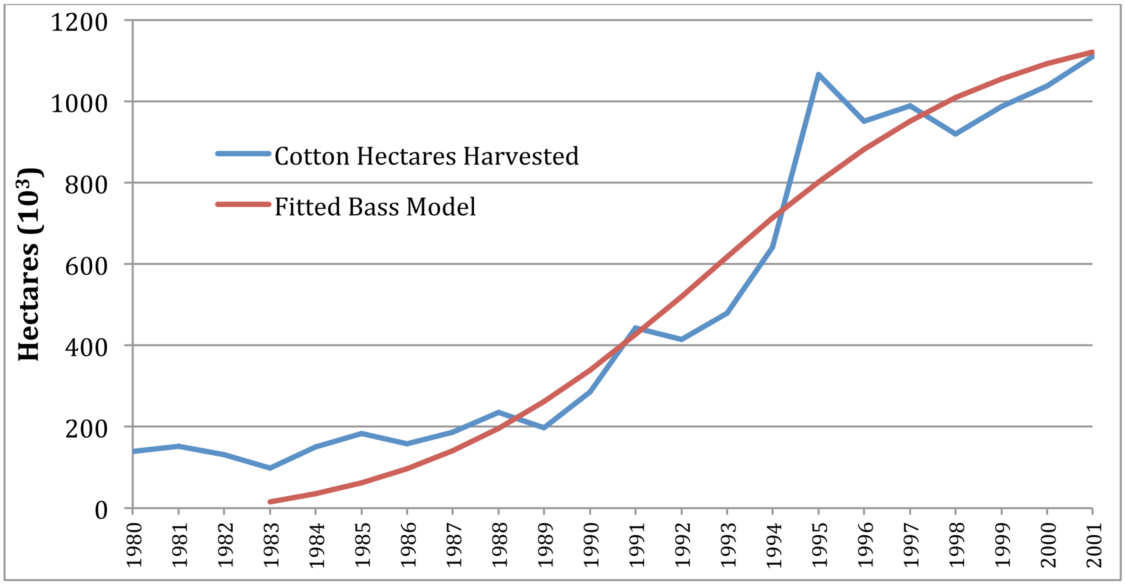


Figure 4.10 Cotton Hectares Harvested in Three-State Region with Fitted Bass Model

The overall conversion of land that breaks even with switchgrass is assumed to follow these same estimates for p and q for all land types even though the analyses above were applied to cropland. No similar proxies are available for the other land types and the contribution from other lands is relatively small (Figure 4.7).

Equation 3 shows the two major components from projecting cumulative switchgrass diffusion annually. The left hand bracketed factor represents the maximum number of hectares that can be converted to switchgrass at a given switchgrass price. The right hand bracketed factor is the cumulative form of the Bass model.

$$SG_{tot}(t) = [BE_{row} \times m_{row} + BE_{past} \times m_{past} + BE_{mar} \times m_{mar} + BE_{hay} \times m_{hay}]\left[\frac{1-e^{-(p+q)t}}{1+\frac{p}{q}e^{-(p+q)t}}\right] \quad (3)$$

Each switchgrass price scenario is used in Equation 3 according to the parameters found for expected switchgrass adoption. The overall diffusion of switchgrass at each price is shown in Figure 4.11 over a 25-year interval. Market saturation levels shown in Figure 4.8 are nearly reached after 20 years. The dominant land type expected to convert for the $100 Mg^{-1} and the $150 Mg^{-1} scenarios is active row crops.

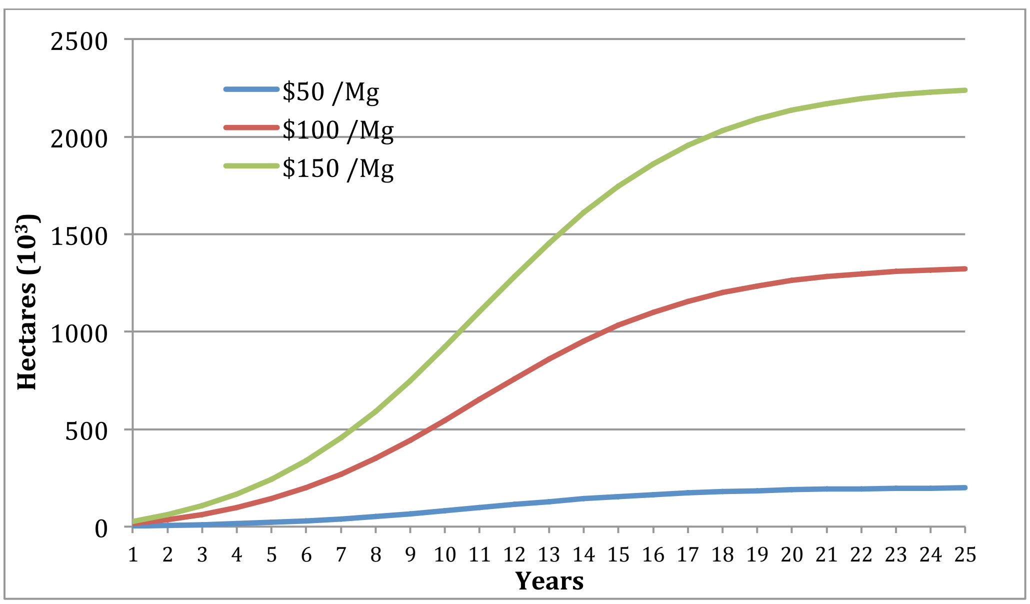


Figure 4.11 Total Regional Diffusion of Switchgrass at $50, $100, and $150/Mg

4.6 Life Cycle Metrics for Switchgrass-to-Ethanol System

4.6.1 Switchgrass Production

For land use change (LUC) effects, measures of net fossil energy, GHG emissions, and nitrogen loss are assessed in terms of GJ ha^{-1} yr^{-1}, kg CO_2e ha^{-1} yr^{-1}, and kg N ha^{-1} yr^{-1}, respectively. Included in land conversion are life cycle impacts of fertilizers and farm equipment use as well as soil carbon flux and nitrogen loss as measures of direct land use change.

A review of literature informs point estimates for the LUC effects with respect to converting each land type to switchgrass. In terms of soil carbon flux, estimates for land types vary between studies and locations. Though point estimates are used for simplification, other factors such as tillage practices may also contribute to significant variability for soil carbon sequestration (Baker et al., 2007; West and Post, 2002). Also, a single value is applied for land in row crops to reflect crop rotations. Assigned values are determined from previous work according to location, land category, and general management practices. A list of sources consulted along with corresponding estimates of soil carbon flux and nitrogen loss when converting land to switchgrass are summarized in Appendix B Tables B.1 and B.2.

Effects from farm energy are also assessed in terms of impacts per hectare. Values for switchgrass and for hay and row crops were collected from previous research on farm energy and GHG emissions for crops in the southeast. Also distilled from these studies were approximate fertilizer usage rates. Point estimates are assessed according to those most appropriate to conditions in the southeastern

U.S. Effects of LUC due to switchgrass are found by subtracting switchgrass estimates from those of row crops and hay. Pastureland and marginal cropland are expected to require a comparatively minimal amount of active farming and are assumed to have no impacts due to farm energies. Sources for farm energy, associative GHG emissions, and fertilizer use are available in Appendix B, Tables B.3 and B.4.

The combination of changes in soil conditions and agricultural effects due to LUC are summarized in Table 4.3. These metrics encompass all of the above impacts associated with converting these lands to switchgrass. Because most studies provide results in terms of unmanaged grassland, findings for this land designation are applied to both marginal cropland and pastureland.

Table 4.3 Land Use Change Effects for Conversion to Switchgrass

Land Type	GHG Emissions ($kg\ CO_2e\ ha^{-1}\ yr^{-1}$)	Net Energy ($GJ\ ha^{-1}yr^{-1}$)	Nitrate Loss ($kg\ N\ ha^{-1}yr^{-1}$)
Grasslands (Pasture/Marginal)	-379	6.6	-5.2
Land in Hay	-1176	-5.5	-6.2
Major Row Crops	-3161	-0.8	-20.6

The values shown in Table 4.3 represent differences in converting unmanaged grasslands, land in hay, and row crops to switchgrass. The GHG benefits of converting unmanaged grassland is minimal. The root system and growth of switchgrass can exceed that of typical grass with added fertilizer, which offer some carbon sequestration advantages as well as improvement in nitrogen loss (Chamberlain et al., 2011). Also, unmanaged grassland is assumed to not require agricultural energy, and managed switchgrass production increases net energy through fertilizer and farm machinery use. The benefit of converting land in hay to switchgrass is largely attributed to less fertilizer use since switchgrass and hay is otherwise similarly managed (Evers, 1998; Franzluebbers and Stuedemann, 2009, 2003). The greatest improvement is converting land in row crop production. Managing a perennial crop reduces farm energy and significantly improves soil carbon (Chamberlain, 2011; US EPA, 2010).

4.6.2 Biomass Transport

Impacts due to transporting large volumes of biomass undermine the benefits of a switchgrass-to-ethanol system in terms of GHG and energy balance. A detailed and comprehensive study distinguishes stages of logistics to assess GHG and energy estimates (Kumar and Sokhansanj, 2007). In concert with values from other biomass transport studies, point estimates of 70 kg CO_2e Mg^{-1} and 0.90 GJ Mg^{-1} are applied to this stage of well-to-wheel production.

4.6.3 Conversion to Ethanol

Units considered for impacts due to the conversion process are GHG and MJ associated with fossil energy per liter of ethanol produced. Even when considering the embodied energy of enzymes which may account for 30-40% of fossil energy in processing cellulosic biomass (MacLean and Spatari, 2009), studies indicate that facilities will produce more electricity than is consumed (Hsu et al., 2010; Spatari et al., 2010). When accounting for electrical power fed back to the grid, greenhouse gas emissions also become negative for the conversion stage. Net reduction values of 0.4 kg CO_2 l^{-1} and 5 MJ l^{-1} serve as general estimates of future probable technologies.

4.7 Aggregate Environmental Impact Results

Using the LUC impacts from Table 4.3 along with the transport and ethanol conversion processes, total impacts can be aggregated according to the land area and corresponding biomass production estimates. Assuming *m*-values are reached for each price level, the total number of hectares for each land type from Figure 4.7 are used to total annual impacts for LUC. Each maximum land area for each price is multiplied by the LUC point estimates given in terms of annual impact per hectare. To translate combined LUC metrics with impacts per biomass, average yields for switchgrass are used for each category of land as in the regional breakeven study, which give total annual biomass production estimates for each price scenario. The conversion of cellulosic material to ethanol is anticipated to be between 70 and 90 l Mg^{-1} of biomass (National Research Council, 2011). A mid-range point estimate of 80 l Mg^{-1} is used to translate total annual biomass into total annual ethanol production.

4.7.1 GHG Emissions and Fossil Energy

Land use change impacts for GHG emissions and fossil energy input are summarized in Figures 4.12 and 4.13. Row crop land diffusion potential far exceeds the other land categories at higher switchgrass prices. The combination of penetration on row crops and the reduction of land use impacts shows that the aggregate environmental effects from LUC are dominated by row crop land. Figure

4.14 shows that taking production to pasture and marginal lands increasing net farm energy. With much more penetration compared to pastureland, marginal land dominates fossil energy impacts in terms of attributed on-farm activity.

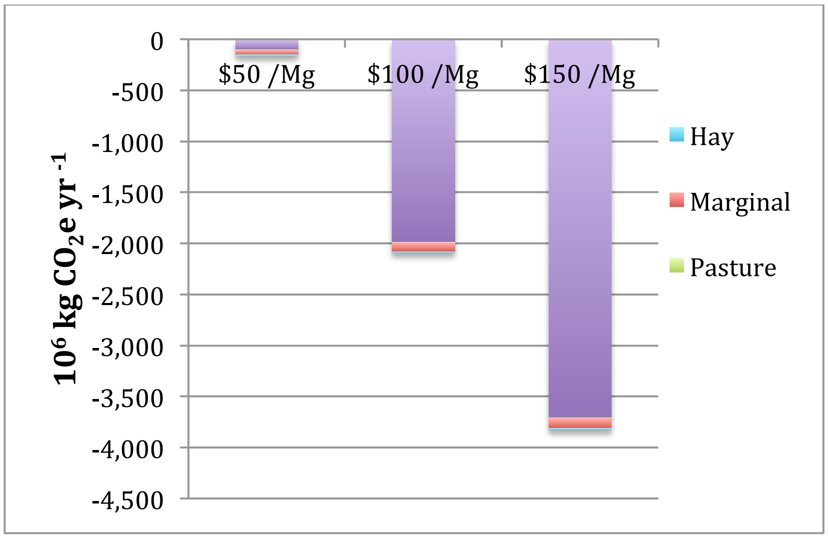


Figure 4.12 Total Annual GHG Emissions Change for Each Price Scenario

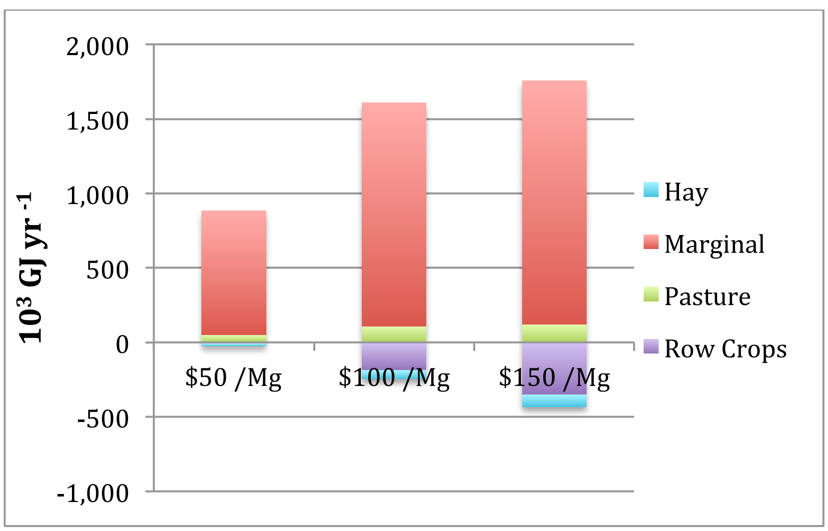


Figure 4.13 Total Annual Fossil Energy Change for Each Price Scenario

Carrying aggregate impact analysis on to the biomass transport and ethanol conversion stages provides a context for the size of these land use change effects. The GHG effects attributed to change in land use practices clearly have an important effect to the overall system. Although, the total amount of emissions in handling and transporting biomass reduce the overall positive effects of LUC and ethanol conversion by approximately a third.

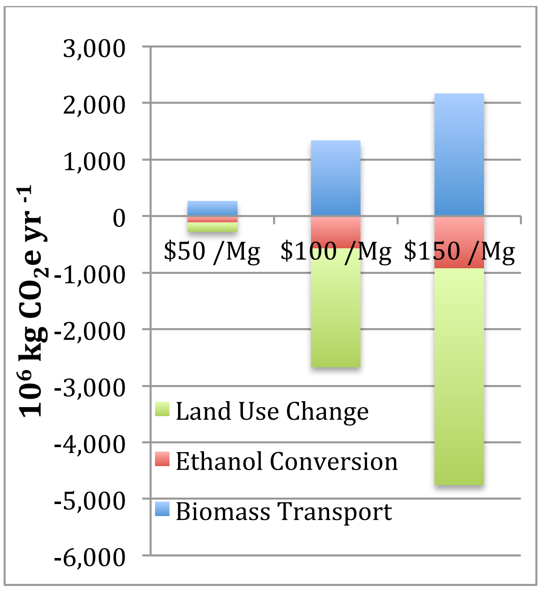


Figure 4.14a Annual GHG Emissions

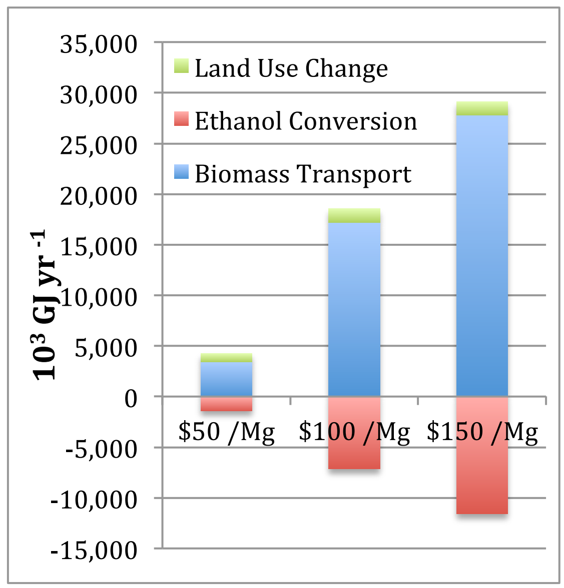


Figure 4.14b Annual Fossil Energy

For net fossil energy, the fossil fuel use in transporting biomass contributes an overwhelming amount compared to other well-to-wheel processes. Changes in on-farm activity has a negligible impact on fossil energy consumption compared subsequent stages. The surplus of electricity generation from the conversion of biomass to ethanol also fails to reduce fossil fuel consumption to net zero.

In terms displacing gasoline consumption with ethanol, this overall system is projected to be a net reducer of fossil energy. For each price scenario, the amount of ethanol generated is approximately 0.7, 5.4, and 9.3 billion liters. When considering only tailpipe emissions and energy density of ethanol versus gasoline, the reduction in gasoline translates to drops in GHG emissions of 1.7, 12.6 and 21.7 billion kg CO_2e yr^{-1}, respectively (National Research Council, 2011; US EPA, 2013b).

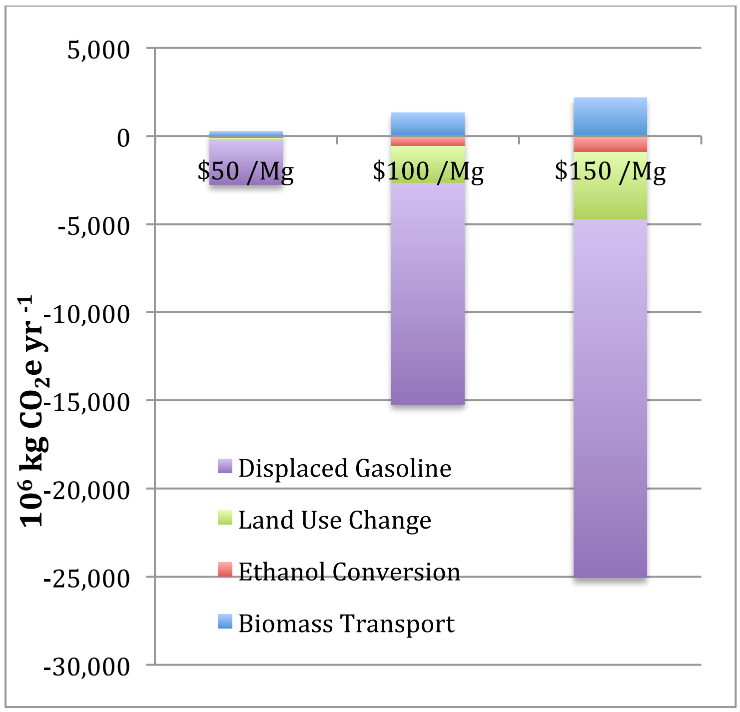


Figure 4.15 Relative GHG Emissions When Accounting for Tailpipe Emissions from Reduced Gasoline Consumptions

4.7.2 Aggregate Nitrogen Flux Over Time

The impact of nitrate loss may have a more immediate impact on the environment. This metric is considered over the course of the twenty-five year diffusion process. Although nitrate loss into natural waters is often a local concern, the entire three-state area used to demonstrate total kg N yr^{-1} reduction over time.

First, the annual decrease at full market penetration of switchgrass is shown in Figure 4.16, where conversion of land in row crops is an overriding contributor.

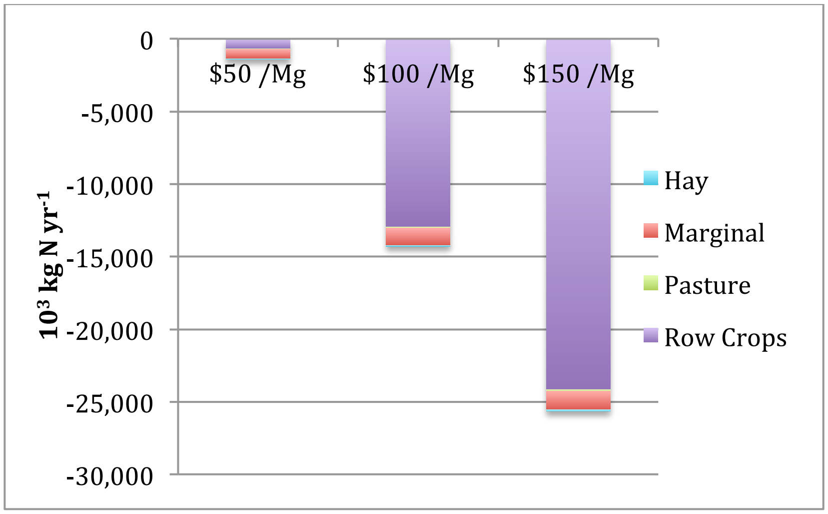


Figure 4.16 Total Annual Nitrogen Change Due to LUC for Each Price Scenario

The short-term nature of nitrate measures is important for reducing eutrophication problems or other similar concerns where loading rates are important factors to the aquatic systems. The rate that row crops are replaced by switchgrass could be important for key watersheds. Using diffusion projections at given switchgrass prices, total annual reductions of nitrate entering waterways in the region are approximated in Figure 4.17.

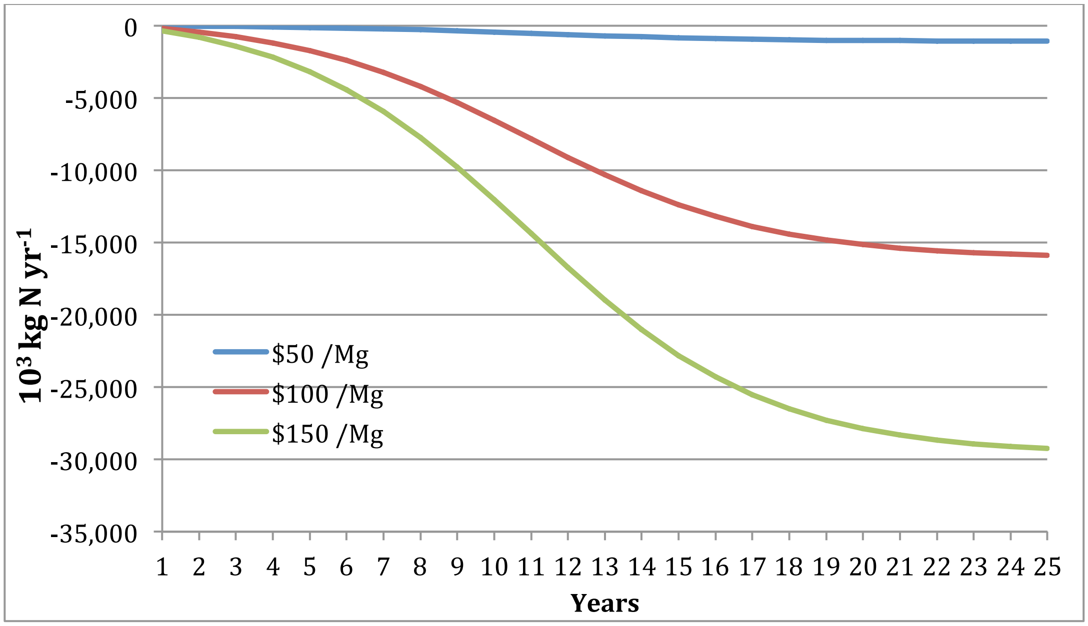


Figure 4.17 Reduction of Nitrate Loss (10^3 kg N yr^{-1}) For Each Price Scenario Projected Over 25 Years

Replacing row crops with switchgrass offers much more potential for reducing nitrogen loss; however, the price of switchgrass must be high enough to initiate land conversion. As the price increases, land conversion is more rapid, which produces a corresponding improvement in nitrate impact. Figure 4.17 shows that at \$150 Mg^{-1}, switchgrass reduces loss by 20 million kg N yr^{-1} after about 11 years. At \$100 Mg^{-1}, 18 years are required to reach the same amount.

4.8 Sensitivity Analysis

When aggregating environmental impacts based on economic conditions, human behavior factors, and LCA estimates, there are a variety of sources of uncertainty. An analysis is conducted to determine the degree of sensitivity for GHG estimates due to land use change in terms of components used in Equation 1 for the three different price scenarios. Subsequent calculations use sensitivity results to show the possible ethanol production under optimistic scenarios given a switchgrass price of $100 Mg^{-1}. From Figure 4.16, the displacement of tailpipe emissions from gasoline is an important component of overall reduction in GHG emissions for the system. An optimistic total ethanol production scenario demonstrate the relative importance of biomass yield advances and biomass-to-ethanol technology in the context of economic, behavioral, and LCA estimates.

Equation 1 approximates the maximum adoption of switchgrass according to breakeven values and *m*-values for the four land categories under each price scenario. Each of the breakeven values depend on expected mean switchgrass yield and a constant switchgrass cost (Sharp and Miller, In Press 2013). Depending on the price of switchgrass, changes in cost and yield can impose significant changes in breakeven area. For a given land category where switchgrass price is near an inflection point along the breakeven curve, a reduction in cost or an increase in average switchgrass yield can generate a dramatic increase in breakeven area (Sharp and Miller, In Press 2013).

For land in hay and row crops, commodity prices were also approximated assuming historical mean yields for each crop remains steady (Sharp and Miller, In Press 2013). If prices were projected to be lower, a greater proportion of land used for hay, corn, cotton, soybeans, and wheat production will be more profitable with switchgrass. As price estimates change, the entire breakeven curves shift as shown in Figure 3.6. When evaluating sensitivity, prices of all four row crops and hay are considered in unison as opposed to examining changes to prices of each crop independently.

Changes to *m*-values have a direct linear effect for maximum switchgrass area for each land category. If the maximum adoption estimates within the breakeven capacity are increased by 20% for all land categories, then SG_{tot} also increases by 20%. For the sensitivity evaluation, the *m*-value for row crop is adjusted while leaving the other three land types constant. Also, a scenario leaves the *m*-value for row crops constant while moving all three other land type *m*-values up 20% and down 20%.

Finally, because the values for GHG emissions due to LUC are estimated on a per hectare basis, aggregated LUC impacts are also multiplicative as with changes to *m*-values. Greenhouse gas emission estimates increase by 20% if the GHG emissions estimate for each land category is increased by 20%.

Figures 4.18 through 4.20 illustrate the changes in aggregate GHG impacts due to land use change as discussed above for switchgrass prices of \$50, \$100, and \$150 Mg^{-1}, respectively. Each factor is independently decreased by 20% and increased by 20% from the reference case used to calculate SG_{tot}. The overall change in GHG emissions is plotted at -20%, the reference case, and +20% for each factor.

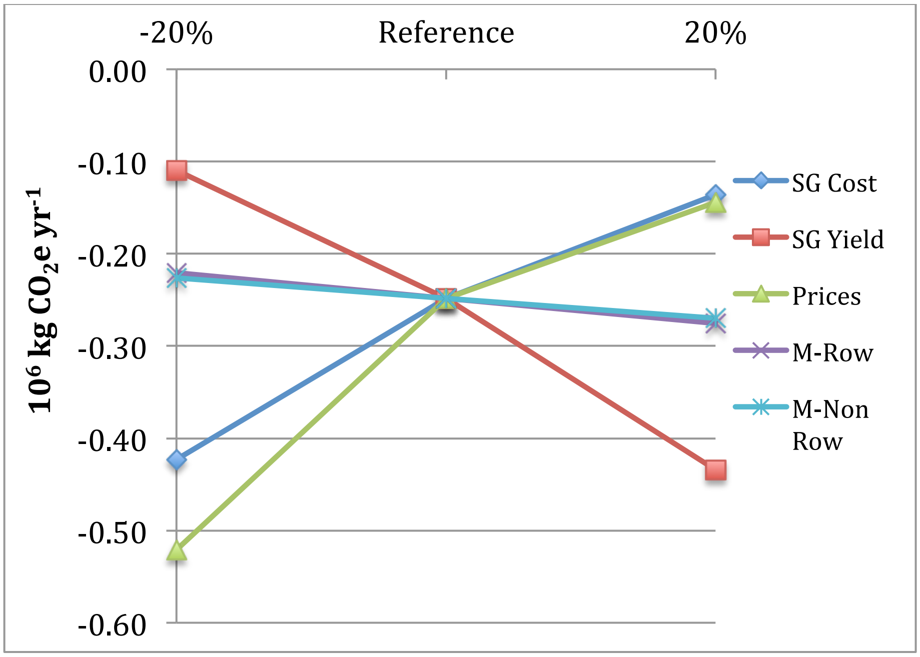


Figure 4.18 Total LUC GHG Emissions Sensitivity According to Components Used to Estimate the Extent of Total Switchgrass Adoption at $\$50Mg^{-1}$

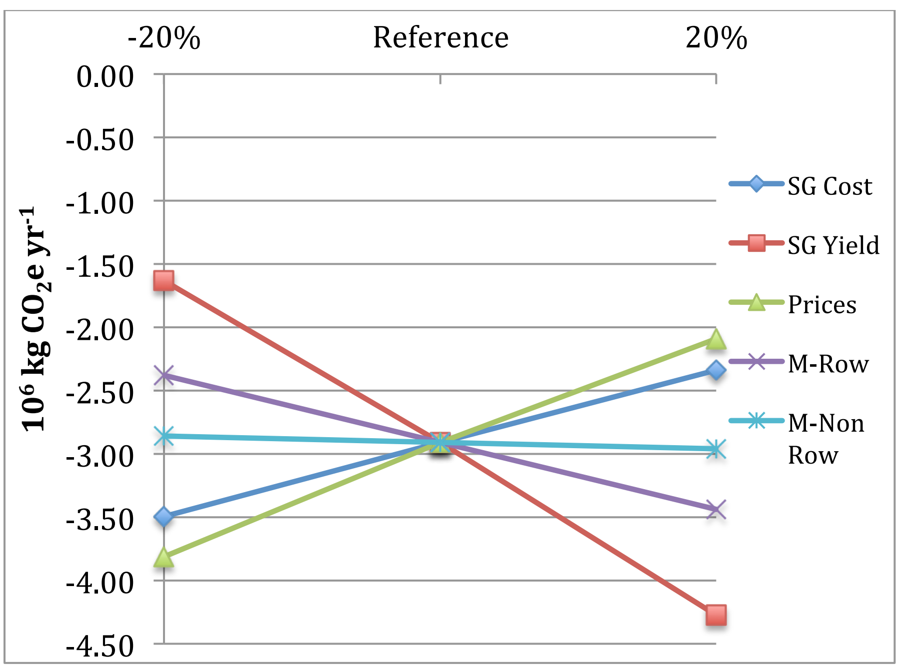


Figure 4.19 Total LUC GHG Emissions Sensitivity According to Components Used to Estimate the Extent of Total Switchgrass Adoption at $\$100Mg^{-1}$

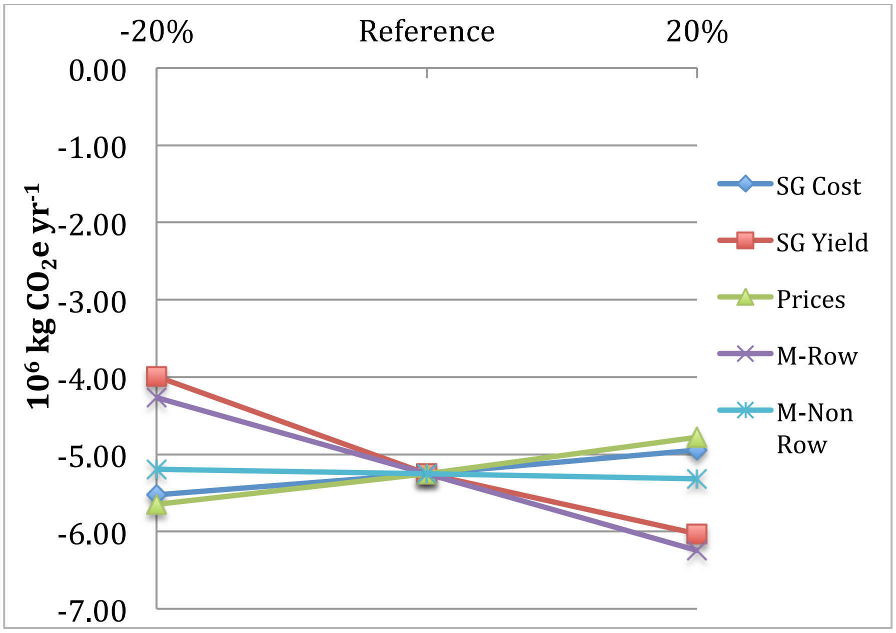


Figure 4.20 Total LUC GHG Emissions Sensitivity According to Components Used to Estimate the Extent of Total Switchgrass Adoption at \$150Mg^{-1}

For each of the plots, increases in switchgrass yield and decreases in prices of traditional crops tend to generate the greatest sensitivity. When switchgrass price is \$150 Mg^{-1}, the effect of commodity price and switchgrass yield is not as pronounced since this price level represents breakeven capacity on nearly all available land in the region. At the extreme upper end of the breakeven curves, changes to price and yield have less impact on breakeven estimates, in which case the maximum extent of adoption on land in row crops produces the greatest effect on total GHG emissions.

Ethanol production at switchgrass price at \$100 Mg^{-1} can be increased by considering advances in switchgrass agriculture and ethanol conversion technology. In a scenario of 20% increase in switchgrass yield, ethanol production for a higher yield scenario increases from 5.4 billion liters to 9.5 billion liters. Improved switchgrass yield has a compounding effect of making switchgrass more profitable as well as generating more annual biomass per hectare. Increased conversion efficiency of biomass to ethanol has also been discussed (National Research Council, 2011). A combination of switchgrass yield and ethanol conversion advances could generate more than double annual ethanol production under the economic and behavioral scenarios analyzed in this paper. The corresponding reduction of gasoline also doubles the annual reduction in GHG tailpipe emissions from 12.6 to about 25 billion kg CO_2e yr^{-1}, which achieves far more GHG reduction than changes depicted in Figure 4.19.

4.9 Discussion

The three pricing scenarios demonstrate dramatically different levels for ultimate size of the industry. At \$50 Mg^{-1} a significant portion of pastureland and hay breakeven, but analysis shows that farmers may have little interest in reworking these land uses for crop production. The nominal amount of marginal cropland in the region offers a relatively small amount of area for production. For land in row crops, this price fails to make switchgrass a more profitable option. Although \$100 Mg^{-1} is a highly optimistic price point (National Research Council, 2011), conversion of significant proportions of land in row crops appears likely a this price level. At \$150 Mg^{-1}, switchgrass is exceptionally profitable and breaks even on nearly all land in the region, but actual land conversion is still expected to be predominantly on land in row crops. At \$150 Mg^{-1}, switchgrass is also expected to diffuse much more rapidly.

4.9.1 Indirect Land Use Change

A potentially important broader consideration for the switchgrass-to-ethanol system for the southeastern US is the effects of indirect land use change (ILUC). With land in row crops anticipated as the dominant land converted to switchgrass, there could be significant consequences that extend beyond the study region in regard to filling a void created by displaced food and fiber production. Net reductions in greenhouse gas emissions as estimated due to direct land use change is optimistic since it does not account for land clearing at national and global levels as a possible consequence of new switchgrass production.

A variety of studies have considered global impacts due to the expansion of bioenergy feedstock production (Hertel et al., 2010; Lambin and Meyfroidt, 2011; Plevin et al., 2010; Searchinger et al., 2008; US EPA, 2010). Different modeling procedures and assumptions produce a wide range of estimates for consequences of indirect land use change. The dynamic nature of carbon debt created from land clearing also compound complexity for applying ILUC assessments to the switchgrass system in the southeastern US (Fargione et al., 2008; Searchinger et al., 2008). Depending on the type of land cleared and the corresponding bioenergy crop, carbon debts can extend for many decades (Fargione et al., 2008).

If the conversion of row crops in the southeast to switchgrass precipitates land clearing, the GHG advantages of from direct land use change could quickly be outstripped by such effects on the global level. For example, the conversion of forest land for the sake of corn ethanol expansion is estimated to result in initial emissions of 604 to 1146 Mg CO_2e ha^{-1} yr^{-1}, which is several orders of magnitude larger than direct land use change estimates for GHG in Table 4.3. The challenge is to evaluate the degree to which switchgrass grown in the southeast could generate such land clearing.

The global relative advantage of converting active cropland to switchgrass is a function of indirect LUC GHG effects, direct LUC GHG effects and downstream impacts such as ethanol production and displacement of emissions from gasoline. The comparative effects of indirect and direct LUC can be evaluated from estimated GHG emission in Table 4.3. If ILUC values per year are projected to be less than 3161 kg CO_2e ha^{-1} yr^{-1}, then it is advantageous to convert row crops to switchgrass when only evaluating in terms of GHG emissions due to all land use change.

The projected ILUC GHG effects could be substantially larger than 3161 kg CO_2e ha^{-1} yr^{-1} when converting active cropland to switchgrass, but the additional GHG reduction when including other life cycle impacts such as the reduction tailpipe emissions from gasoline also provides much larger GHG benefit than only including LUC effects. The conversion of marginal land to switchgrass could be assumed to be negligible because of a lack of competition with other land uses. Pastureland and land in hay might also be assumed to have a comparatively insignificant impact on indirect LUC because the small amount of land converted at any switchgrass price is likely within margins for eliciting indirect LUC (Plevin et al., 2010). Depending on the value of for ILUC due to the conversion of land in row crop to switchgrass, there may be levels of switchgrass prices that generate an optimal mix of land conversion such that the overall GHG effect is maximized. The direct LUC for converting row crops to switchgrass has a greater estimate for reducing GHG emissions than the other land types. Also, the expected average yield is higher, which implies greater potential to generate ethanol and reduce tailpipe emissions per hectare. However, broader conditions dictate a potential threshold for which converting additional row crops to switchgrass may generate detrimental land clearing that could exceed GHG life cycle benefits from well to wheel.

Using values for the \$100 Mg^{-1} scenario for switchgrass, it is possible to roughly calculate maximum ILUC values that create a net global release of GHG emissions from converting land in row crops. The total projected net GHG reduction is about 15,000 10^6 kg CO_2e ha^{-1} yr^{-1}. About 1.4 million hectares are necessary to achieve such an outcome of which 0.8 million hectares are land in row crops. The implication is that row crops is responsible for about 12,500 kg CO_2e yr^{-1} reduced GHG emissions per hectare. Indirect LUC values that are estimated above 12,500 kg CO_2e yr^{-1} per hectare of displaced land in row crops imply a net GHG disadvantage when converting each hectare of row crops to switchgrass. Otherwise, in terms of GHG emissions, the optimal outcome is have the highest potential price for switchgrass in order to induce the conversion of as much land in row crops as possible.

4.9.2 Considerations at a Static, Maximum Level of Adoption

The consideration of adoption in conjunction with LCA results of an emerging system brings to light two general perspectives for aggregating impacts. The first perspective is concerned with total effects at estimates of maximum market penetration. The second perspective is associated with total effects throughout the duration of the diffusion process. For many applications, time plays an important role in policy implications. In some instances, environmental concerns may be associated with temporal concentration levels or thresholds that have more immediate relevance to adoption rates. The scenario of $100 Mg^{-1} switchgrass is used for discussing aggregate impacts and the rate of adoption.

Greenhouse gas emissions, fossil energy, and gasoline displacement generated by the system are considered at the cumulative adoption endpoint. A key interest is the estimated total amount of ethanol derived from switchgrass for the region. At $100 Mg^{-1}, eventual production is expected to reach about 5.4 billion liters per year. With about 45 billion liters of gasoline consumed in the region each year, this amount of ethanol displaces about 9% of gasoline (EIA, 2011).

With about 0.8 million hectares of row crops displaced to achieve this percentage, significant environmental improvements to the region can occur through transitions in agricultural activity. The combination of reduced farming intensity and carbon sequestration associated with converting this land to a perennial crop with a deep root system has important GHG impacts. Annual reductions of about 2 billion kg CO_2e yr^{-1} are attributed to LUC impacts. Reductions in GHG emissions from gasoline tailpipe emissions is approximately 12.6 billion kg CO_2e yr^{-1}. Additionally, advancing switchgrass yield and ethanol conversion technology could boost the maximum the reductions in GHG emissions and accelerate switchgrass adoption through increased profit.

In terms of the other stages of the well-to-wheel life cycle, it is useful to consider the fossil-fuel intensive process of transporting and handling the huge volumes of biomass that are required to produce such large quantities of ethanol.

The consumption of fossil energy attributed to on-farm activities is comparatively small. While the conversion of biomass to ethanol has a net reduction of about 7 million GJ yr^{-1}, this amount is far outweighed by the machinery used to manage collection and delivery of a highly distributed form of energy with a relatively low level of energy density.

4.9.3 Considerations for Time-Dependent Nature of Adoption

In terms of environmental impacts over time, nutrients entering natural waters are subject to time-dependent thresholds and can often be improved relatively quickly when loadings are reduced (Diaz and Rosenberg, 2008). Policy targeted at reducing such effects implies attention to adoption rates. Results show that there is potential for expediting reduction to nutrient loadings by elevating profit potential with switchgrass. Increasing the switchgrass adoption rate is one way to manage water quality in the short term without harming farmer profits for row crops by regulating fertilizer use.

The rate of adoption in the case study may have greater implications in relation to policy and the nature of trends of technological transitions. The Renewable Fuel Standard has targets for the year 2022. Results suggests that the maximum adoption scenarios are relevant to RFS goals only in terms of the rate of adoption. To reach full adoption under the breakeven scenarios, switchgrass diffusion will take substantially longer to attain. As far as the southeast contribution to the biofuel production targets, a region consisting of Alabama, Arkansas, Florida, Georgia, Hawaii, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas is estimated to contribute 40 billion liters of cellulosic ethanol largely derived from perennial grasses (USDA, 2010). According to diffusion estimates, the three states of the current study (Georgia, North Carolina, and South Carolina) will only be able to contribute a tiny fraction of that amount using switchgrass according to the RFS timeframe.

On a broader time scale, there are further implications of diffusion rates. For some researchers, biofuels are considered a transition technology for transportation energy (Geels, 2012). Diffusion of new technologies is influenced by emergence of new generations of technology and other competing options (Peres et al., 2010). Such diffusion of innovation concepts suggest a timeframe for initiating adoption of biofuel technology and generating sufficient momentum to achieve meaningful levels of adoption (Geels, 2012). If diffusion is too slow, other technology options may overtake biofuels as a transport energy.

5 SUMMARY

5.1 Contributions of Research

Environmental impact is defined by humans acting on the natural world, yet life cycle evaluations of complex systems often fail to include human behavior as part of the analysis. The contribution of this research is further development of comprehensive environmental assessments by integrating approaches that quantify economic and social aspects of emerging systems. The case study of a switchgrass-to-ethanol system for a region of the southeastern U.S. is an appropriate case study because the behavior of prospective growers serves an important role for the overall environmental outcome of the industry.

Assessing environmental impacts of emerging systems is valuable because knowledge about anticipated environmental effects prior to a new system becoming established allows for greater potential to proactively manage development. Well-informed policy and regulations can help to avoid unintended outcomes. For example, expanding production of dedicated bioenergy feedstock has generated concerns for carbon debt due to land clearing and possible impacts to food and fiber production (Fargione et al., 2008; Tilman et al., 2009). Early understanding of social, economic, and environmental implications during the development process of new technologies is useful for devising effective management strategies that reduce prospective negative consequences.

The novel approach proposed in this research is the incorporation of diffusion of innovation into LCA. Examining adoption behavior provides key insights into how an emerging technology is deployed and the extent that it expands. Comprehending such processes have important implications on the overall environmental impact posed by an new innovation. Without details on how an innovation is integrated with existing systems, aggregated LCA results are based on guesswork. Instead, this work proposes techniques that can maximize available data through diffusion modeling along with other statistical methods.

Policy directed toward environmental concerns is often driven by impact targets and timelines. As illustrated in the switchgrass case study, the rate of cumulative switchgrass adoption shows that it may take about 20 years before switchgrass begins to approach maximum penetration levels. Initiatives such as RFS mandates have sooner targets which imply that additional financial incentives are necessary to expedite industry growth. For example, when modeled at an exorbitant switchgrass price of \$150 Mg^{-1}, switchgrass diffusion is expected to be much more rapid. Otherwise, findings from this research suggests that RFS goals were not practical according to the diffusion of innovation assessment for switchgrass expansion.

5.2 Research Summary and Limitations

This work addresses the three central components of sustainability for the switchgrass system. In Chapter 2, the influence of social mechanisms is reviewed in terms diffusion of innovation where the effects of social contagion shape adoption trends of new technology. In Chapter 3, the economic prospect of the system is viewed from the perspective of farmer's propensity to profit from switchgrass. In Chapter 4, previous evaluations of environmental impacts on a per unit basis are collected in order to aggregate the overall effect that the system may have in the region according to expected social and economic conditions of switchgrass production.

The review of diffusion of innovation literature shows that a macro-level model is more appropriate than micro-level models for analyzing switchgrass diffusion. With a limited amount of detailed data for switchgrass adoption, the Bass model is an attractive option for diffusion analysis. Evaluating the nature of social contagion within the regional farming community is relatively straightforward. Historical adoption trends show that profitable agricultural practices tend to be adopted at a fairly predictable rate on cropland. Sophisticated micro-level approaches such as agent-based models do not fit this system because no evidence supports the need for models that provide insight into emergent behavior. The challenge for this application is not to coordinate complex modeling tools, but to manage assumptions relative to available agricultural economic data.

A key limitation to this study is the lack of a switchgrass market. To motivate the adoption study in conjunction with possible environmental effects, I assume that the market would exist in the region. This supposition implies that a mechanism for adjusting switchgrass price must be instituted in order to manage subsequent assessments of the prospective system. The breakeven study is unique from similar analyses in that price is allowed to vary and the probable magnitude of production is assessed according to price as an independent variable. This approach allows for analysis of capacity on different types of land, which has implications for land use change impacts and switchgrass yield without being constrained by an arbitrary pricing structure.

Results of the breakeven analysis show that pastureland has significant potential for breaking even with switchgrass at lower prices whereas much higher prices are needed to compete with expected profits from row crops. Marginal cropland and land in hay also break even at lower prices, but the relative volume of land is dramatically lower than that of pastureland. The breakeven analysis develops a framework for exploring how farmers may actually adopt switchgrass.

An important simplification is that the breakeven results do not incorporate the dynamics of profitability. Though commodity prices were projected (Appendix A), they were pinpointed to a range at five years from the most recent pricing data. The decision to use single price estimates for a point in time alleviates a significant source of complexity due to markets that are subject to substantial annual fluctuations. Instead, the focus of the analysis is toward assessing variability of expected yields between and within the types of land in the region.

Before analyzing the rate of switchgrass adoption, the maximum level of switchgrass penetration within breakeven capacities at \$50, \$100, and \$150 Mg^{-1} were addressed. Diffusion of innovation documents the difficulty of judging the extent of market penetration of new technologies before they are released. For switchgrass, profitability from row crops was used as an explanatory variable for gauging the degree that switchgrass is grown on the different land types. Regression analysis showed that pastureland and land in hay have resisted conversion to row crops despite significant fluctuations in potential profit. Historically, land in row crops and marginal has been more responsive to potential profit as seen from annual crop selection according to crop prices.

The amount of land in row crops that is converted is expected to be the primary driver of the industry's size. This is an important finding because the land use change effects in terms of GHG emissions and nitrate loss are considerably better when reducing the amount of intensively farmed land with switchgrass.

In terms of the rate of adoption, the Bass model is fit to previous applications of adoption in agricultural. The reemergence of cotton hectares in the region is a convenient event for approximating the diffusion of switchgrass. Parameters fit to the diffusion of this cotton example provide an approximate trajectory of switchgrass adoption, which is in line with historic agricultural adoption trends. A final diffusion model uses the approximations for maximum adoption along with the estimated Bass model parameters to illustrate how land may be converted to switchgrass over time.

Environmental impacts are aggregated from two perspectives. First, static results are assessed at the expected full market penetration levels for the three different prices. The rate of switchgrass diffusion offers chronological information for both aggregate impacts and policy perspectives.

Impacts at maximum adoption estimates are considered at \$100 Mg^{-1}, which is a decidedly optimistic farm-gate price. At this level, the displacement of gasoline projected to be only about 9% of the regional annual rate of consumption. Yet, the reshaping of the agricultural industry by converting a million hectares of actively farmed row crops could have important impacts for overall nitrogen loss to aquatic systems and soil carbon sequestration. The annual net effect of converting these lands to switchgrass may achieve about one sixth of the GHG reduction from displacing gasoline tailpipe emissions.

Effects of eutrophication is an environmental concern that could be addressed in the short term due to LUC effects of converting intensively farmed land to switchgrass. Estimating the rate of switchgrass adoption is of greater interest for near-term environmental impacts.

The profit-driven analyses heavily relied on USDA NASS data. With county-level data, profitability of crops can generally be assessed with a relatively high degree of certainty; however, for some data, profits and land areas were difficult to determine. For example, annual data on hay harvests were unreliable and were not detailed in terms of the variety of forages that were grown. This lack of information posed a challenge for comparing bermudagrass profits with that of switchgrass.

Finally, broadly applying life cycle assessment results to the region requires enormous assumptions, especially with regard to LUC effects. LCA estimates have been determined on pilot scales and models, which must be properly extrapolated and applied. For example, the application of switchgrass carbon sequestration rates to different land categories described by USDA is a complex affair as described by Chamberlain (Chamberlain, 2011). The precise level of LUC effects and downstream processes that affects of GHG emissions and net energy are highly variable and subject to possible shifts in technology and LCA interpretation.

5.3 Future Work

There is an overarching need to structure assessments of emerging technologies that include human behavior with in the LCA framework. Particularly for managing complex systems such as the switchgrass-to-ethanol application. The prospective cellulosic industry for the southeastern US combines the energy sector, the agriculture industry, and a diverse set of stakeholders, which include different tenures of farmers, investors, and policy makers. Despite the complexity, there are two possible methods for advancing toward a more representative analysis. First, the breakeven assessment could be transitioned to a more dynamic approach. The previous examples of adoption in agriculture suggest that the social component to the comprehensive assessment is straightforward. Farmers will, in time, convert land in row crops to the most profitable option. The greater challenge is to determine the degree of switchgrass profitability over other crops. This type of system could be modeled by Markov Chain Monte Carlo (MCMC) methods.

Using Markov Chain Monte Carlo analysis, the diffusion approximations could better capture error in a dynamic sense. An MCMC approach can help manage aleatoric uncertainty by demonstrating variances through simulation results. For example, error bars can be incorporated on the breakeven curves while also including a dimension for time. Furthermore, MCMC provides a convenient structure for performing simulations with what-if scenarios.

In an agricultural economic setting, MCMC offers an iterative evaluation to seasonal fluctuations in yield, costs, and commodity prices. Performing many simulations for year-to-year profits captures nuances to the comparative attractiveness of growing switchgrass. The breakeven analysis used in the study simply evaluated prospective profit of major row crops and hay at a single point in the future. Showing how profit for any given growing season in the future may increase and decrease is advantageous for understanding farmer risk and average profit at different switchgrass prices. Profit calculations that include annual volatility could provide a more realistic representation of breakeven potential along with subsequent switchgrass adoption.

To strengthen diffusion assessments, the use of data from analogous systems could also be an important consideration. Bayesian data analysis is an approach that uses prior distributions to parameters that otherwise have minimal data for parameter estimation. Also, given the time-dependent nature of data, Bayesian analysis is appropriate because it offers a convenient structure for updating estimates as new data are made available.

An emphasis on geographic location of potential switchgrass production is another possible direction for this work. Because the USDA offers county-level data, there is opportunity to highlight specific areas within the three-state that are likely to be prominent switchgrass producers. Additional spatial assessments could be useful for both environmental and economic reasons.

Locating ethanol conversion facilities can optimize reductions in biomass transport along with corresponding emissions and fossil energy. In terms of LUC effects, concerns about eutrophication can be addressed by mapping watersheds that may offer greater adoption of switchgrass.

A key issue for USDA support of biofuel expansion is developing rural economies (USDA, 2010). Outlining specific locations for ethanol conversion facilities and switchgrass production can be combined with data on economic conditions. For example, some counties within the study region have poverty rates that are greater than 30% (US Census Bureau, 2010). Combining spatial production knowledge with economic data allows for strategic targeting of industry growth to maximize economic benefit.

Combining diffusion of innovation with dynamic LCA implies challenges for projecting outcomes for complex systems. Bayesian data analysis in concert with stochastic methods such as MCMC are potential tools for improving this research; however, there are more fundamental concern is establishing a familiar structure for LCA that includes diffusion analysis of emerging technologies. Though the assessment of environmental impacts of a new innovation that includes the economic and social setting of the system is important for transitioning to a sustainable future, the area of research has a limited history from which to compare methods and assessment results. The future of comprehensive analysis of emerging technologies will require standardization in a similar way that other LCA techniques, such as CLCA, have been accepted internationally (Guinée et al., 2011).

5.3 Concluding Statements

In recent decades, there has been discussion of the urgency to transition to alternative sources of energy, yet there are challenges to successfully implementing solutions in a paradigm where production and consumption of energy is largely dictated by economic convenience as opposed to proactively incorporating ecological value. Path dependency, social and political inertia, and increasing returns from lock-in reduce the priority of managing energy according to potential strains on the ecosystem. While LCA of proposed solutions provide an accounting of total environmental costs and benefits, there must be further analysis that characterizes the displacement of existing regimes and the extent of diffusion. Such investigations can suggest pathways to favorable social and economic circumstances that imply well-intentioned adoption over a long term and realize meaningful environmental improvement.

As noted by David Mackay, "If everyone does a little, we'll achieve only a little. We must do a lot." (Mackay, 2009). In order to know what a lot is and how it might address critical environmental effects, we must become more proficient at assessing potential solutions in terms of the total life cycle impacts that include human behavior as part of the calculation, and then consider results in the broader political and environmental context.

APPENDICES

Appendix A. Yields, Costs, and Price Analysis for Estimating Maximum Land Use Change Potential in Georgia, North Carolina, and South Carolina

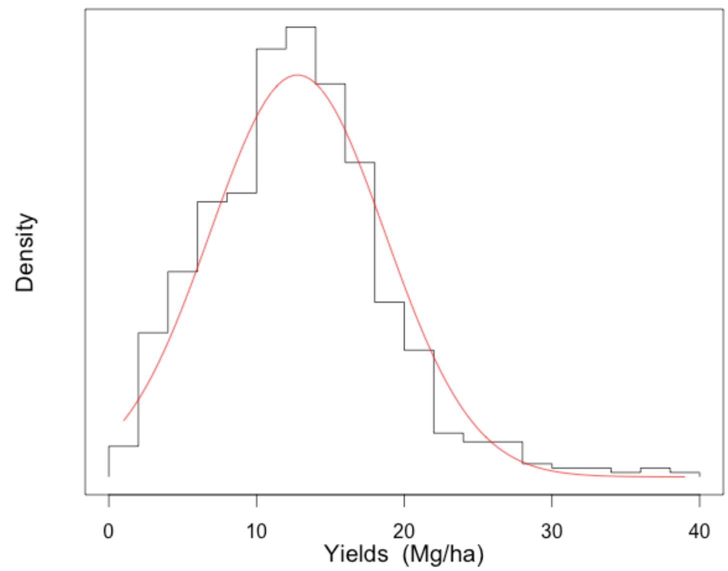


Figure A.1 Approximate Histogram and Normal Distribution Fit to Lowland Switchgrass Yield Data from Wullschleger et al. (2010).

Table A.1 Switchgrass Cost Estimates per Hectare from Published Studies and University Budgets

Reference	Location	$ ha^{-1}[a]
Khanna et al., 2008	IL	400.28
Perrin et al., 2008	ND, SD, NE	181.03
Larson et al., 2010	Southeast	638.46
Duffy, 2008	IA	614.81
Clemson Extension, 2010	SC	669.37
NC State Cooperative Extension, 2008a	NC	738.61
Ferland, 2001	GA	649.61
UT Extension, 2009	TN	655.36

[a] Estimates include annualized establishment costs over 10-year period and exclude annual land charges. The value from Larson et al. is found by multiplying the average yield of 12.9 Mg ha^{-1} by the estimated costs per Mg.

The cost used in the study to represent the three-state region is $625 ha^{-1} in the reference case and $400 ha^{-1} under a scenario of low-cost production.

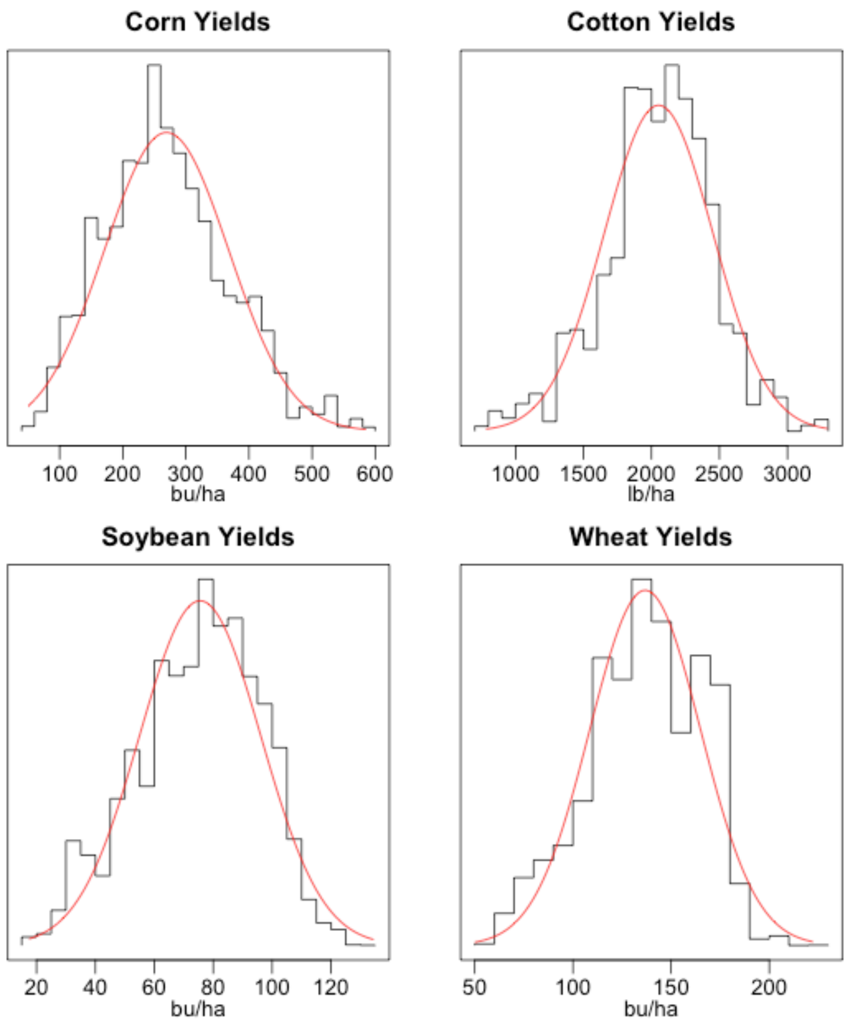


Figure A.2 Histograms of the Average County Yields (2007 – 2012) Weighted by Harvested Area with Fitted Normal Distributions (USDA NASS, 2013)

Table A.2 Average Variable Costs from University of Georgia, North Carolina State University, and Clemson University Available Enterprise Budgets.

Crop\Year	2008	2009	2010	2011	2012	Average
Corn	733.41	1075.71	918.48	938.18	965.38	926.23
Cotton	1136.45	1338.07	1195.48	1152.90	1236.15	1211.81
Soybeans	450.60	620.52	540.31	687.03	694.18	598.53
Wheat	505.39	745.16	616.22	616.22 [a]	596.03	615.80

[a] Sufficient wheat cost data for 2011 were not readily available. 2010 estimate used.

Conservation tillage and non-irrigated values were generally recorded if available.

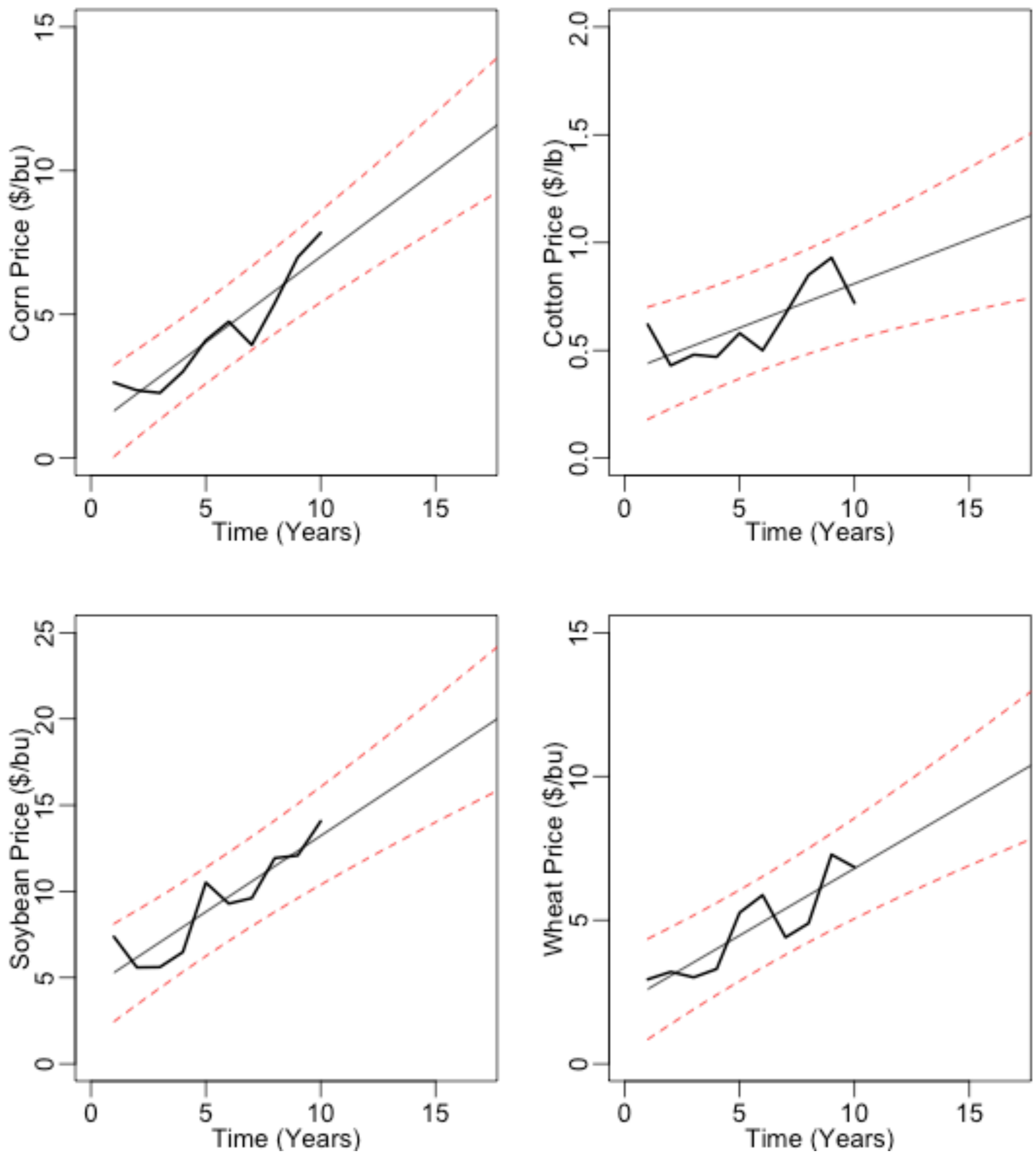


Figure A.3 Project Crop Prices 90% Prediction Intervals For Corn, Cotton, Soybeans, and Wheat (USDA NASS, 2013)

For these data, year 15 corresponds to 2017 market year prices for which the predicted value and interval values are used to calculate expected profits.

Table A.3 Summary of Row Crop Parameters for Calculating Net Revenue Distribution

Crop	Projected Price ($)	Price StdDev	Mean Yield ha^{-1}	Yield StdDev	Cost ($\$ ha^{-1}$)	Weight[a]
Corn (bu)	9.99	1.09	270	98.5	926.23	0.203
Cotton (lbs)	1.01	0.18	2053	400	1211.81	0.305
Soybean (bu)	17.63	1.95	75.5	20.6	598.53	0.318
Wheat (bu)	9.13	1.20	137	28.3	615.80	0.174

[a] Net revenue is weighted by area harvested in 2012.

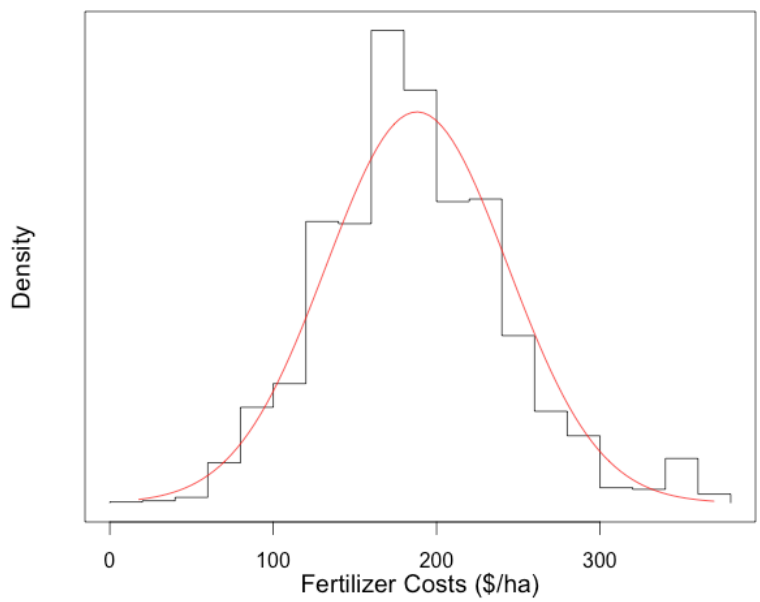


Figure A.4 Histogram of Average County Fertilizer Expenses per Hectare Weighted by Cropland Area with Fitted Normal Distribution (USDA NASS, 2013)

The above distribution with mean $188 ha^{-1} and standard deviation $56 ha^{-1} is adjusted to represent fertilizer expenses for bermudagrass according to values from Table A4 below.

Table A.4 Annual Fertilizer Costs for Bermudagrass from University Budgets

University	Fertilizer Costs ($/hectare)
Clemson Extension, 2012	1054.69
NC State Cooperative Extension, 2008b	657.69
University of Georgia Extension, 2012	489.80
Alabama Cooperative Extension, 2008	977.45
The University of Tennessee, 2007	471.94
Mississippi State University Ag Economics, 2008	543.40
Average	699.16

The distribution in fertilizer costs for bermudagrass is represented by a normal distribution with mean $700 ha^{-1} and standard deviation $208 ha^{-1}.

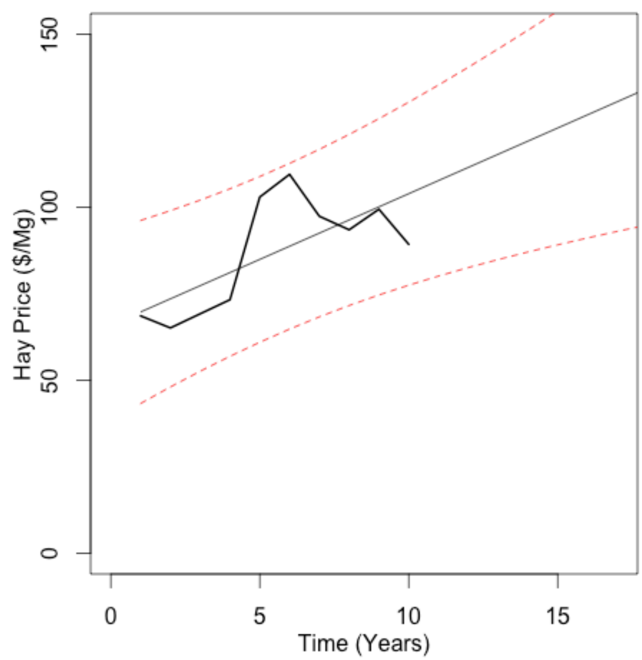


Figure A.5 Projected Hay Prices and 90% Prediction Interval (USDA NASS, 2013)

For these data, year 15 corresponds to 2017 market year prices for which the predicted value and interval values are used to calculate expected profits.

Appendix B. Impacts of Land Use Change to Switchgrass

Table B.1 References for Nitrate Loss and Differences Compared to Switchgrass

Crop	Reference	N Loss (kg N/ha)	SG Difference (kg N/ha)	Comments
Switchgrass				
	(Chamberlain et al., 2011)	5		Table 2. 5 kg N/ha-yr @ 90 kg N
	(Sarkar et al., 2011)	**1.77**		10 yr avg. taking young (7) SG vs established (1.2) in account. At 90 kgN. p 4378
Hay				
	(Franzluebbers and Stuedemann, 2003)	8	**-6.2**	2.7 g N/m2 in OH and .3 to 1.2 g N/m^2 in NC. Study N leaching by soil depth
Corn				
	(Miller et al., 2006)	**35.7**	**-33.9**	median from literature and modeled
	(David et al., 2008)	28	-26.2	corn-soybean agroecosystem
	(Kalita et al., 2006)			average over 5 plots in IL ~ 26
Soybean				
	(Miller et al., 2006)	**16.4**	**-14.6**	avg from literature and modeled
	(David et al., 2008)	28	-26.2	corn-soybean agroecosystem
Cotton				
	(Chamberlain et al., 2011)	59	-56.6	Table 2. (Tilled Crops) 59 kg N/ha-yr
	(Sarkar et al., 2011)	**15**	**-13.2**	90 kg N. p .4378
Wheat				
	No references found	**22.4**	**-20.6**	Since rotated among other, avg above 3 crops
Unmanaged Grassland				
	(Chamberlain et al., 2011)	8	**-5.2**	Table 2. 5 kgN/ha-yr @ 90 kg N, Table 1 has -5.2 kg/ha-yr

Bold values indicate those used for calculating differences for converting crops to switchgrass

Table B.2 GHG Emissions due to Carbon Soil Flux and from Converting Land to Switchgrass

Crop	Reference	GHG Flux ($kgCO^2\ ha^{-1}yr^{-1}$)	SG Diff GHG ($kgCO^2\ ha^{-1}yr^{-1}$)	Notes
Switchgrass				Carbon sequestered: -40 gC/m2-yr = 1470 kgCO2/ha-yr
	(Adler et al., 2007)	-1270		Nitrous: 20 gCO2e/m2-yr=200 kg CO2/ha-yr
	(Davis et al., 2011)	-1800		At 70 kg N/ha -25 to -75 g C/m2-yr to 2020 on color map GHG -917 to -2750 kg CO2e/ha-yr
	(Robertson et al., 2011)	-550		Fig 2,3,4 Tilled cropland 15 gCO2-C/m2yr (also CRP 0, and Prairie 25)
	(Ma et al., 2000)	-1762		Alabama 0.48 Mg C/ha-yr = 1762 kg CO2/ha-yr (from Franz 2005 table 8)
Hay				
	(Franzluebbers and Stuedemann, 2009)	-350	**-920**	Hay in the Peidmont avg of 3 areas 0.20 Mg C/ha-yr (-.06, .24, .39), fertilized with poultry litter
Corn				
	(Adler et al., 2007)	-618	-652	Corn-Soybean rotation-no till: Fig 2 approx near-term before equilibrium
	(Davis et al., 2011)	0	-1270	GHG -917 to 917 kg CO2e/ha-yr projected to 2020
	(Robertson et al., 2011)	367	-917	Crop to switchgrass Fig 2 (Iowa) Corn-soy rotation no till Diff between NT and SG = ~ 25 gCO2-C/m2yr=-917
	(Kim et al., 2009)	800	-2070	Fig 2 4 No-till sites in corn belt, approx avg of 100 g CO2/kg grain Yield is approx 8,000 kg /ha => +800 kg CO2/ha
Soybean				
	(Adler et al., 2007)	-618	-652	Corn-Soybean rotation-no till: Fig 2 approx near-term before equilib
	(Robertson et al., 2011)	367	-917	Crop to switchgrass Fig 2 (Iowa) Corn-soy rotation no till Diff between NT and SG = ~ 25 gCO2-C/m2yr=-917
Cotton				
	(Chamberlain et al., 2011)		**-3130**	Table 1. Difference at 90 kg fert =313 gCO2/m2-yr (-3,130 CO2 kg/ha-yr)
Unmanaged Grassland				
	(Chamberlain et al., 2011)	-520	**-750**	Table 2. Change in SOC at 20 cm = 3 gC/m2-yr (-110 kg CO2/ha-yr) Table 1. Difference at 90 kg fert = 75 g CO2/m2-yr (-750 CO2 kg/ha -yr)
	(Robertson et al., 2011)		-917	Prairie to other switchgrass Fig 4 (Kansas)

There is a wide range of strategies and presentation styles related to carbon soil flux. Results depend on soil depth measurements, tilling practices, and resolution for location. Furthermore, annual crops are rotated making differences between them less important than the overall effect converting to switchgrass. The primary assessment used in this study is from Chamberlain et al. 2011.

Table B.3 References for Fertilizer Usage and Impact Differences Compared to Switchgrass

Crop	Reference	Location	Fert Rate (kg ha^{-1} yr^{-1})	SG Diff GHG (kg CO2 ha^{-1} yr^{-1})	SG Diff Energy (GJ ha^{-1} yr^{-1})
Switchgrass					
	(Chamberlain et al., 2011)	SC	**90**		
	(Adler et al., 2007)	PA	56		
	(Ma et al., 2000)	AL	112		
	(Schmer et al., 2008)	Midwest	avg 74		
	(Robertson et al., 2011)	KA	70		
	(US EPA, 2010)	N/A	113		
Hay					
	(Franzluebbers, 2005)	Southeast	225		
	(Evers, 1998)	Southeast	**200**	-372	-6.3
	(US EPA, 2010)	N/A	181		
Corn					
	(USDA NASS, 2013)	GA,NC, SC	**150**	-172	-3.4
	(US EPA, 2010)	N/A	119		
Soybean			**0**	257	5.1
	(US EPA, 2010)	N/A	10		
Cotton					
	(Chamberlain et al., 2011)	SC	**90**	0	0.0
	(USDA NASS, 2013)	GA,NC, SC	90		
	(US EPA, 2010)	N/A	85		
Wheat					
	(Frederick et al., 2001)	SC	**90**	0	0.0
	(US EPA, 2010)	N/A	79		
Grassland					
	Assumed No Ag Input	N/A	**0**	257	5.1

Bold values indicate those used for calculating differences for converting crops to switchgrass. Fertilizer values translated to emissions using Energy Information Administration values of 56.9 MJ kg $^{-1}$ N and 2.86 kg CO_2e kg^{-1} N.

Table B.4 References for On-Farm Emissions and Fossil Energy Consumption

Crop	Reference	Farm Machinery Energy (kg CO2 ha^{-1} yr^{-1})	Farm Machinery Emissions (GJ ha^{-1} yr^{-1})	Comments
Switchgrass				
	(Adler et al., 2007)	**1.5**	**114**	Additional Harvest
	(Schmer et al., 2008)	1.2		Diesel + machinery energy 882+283
Hay				
	(Adler et al., 2007)	**0.7**	**55**	avg between canary grass and alfalfa (2 harvests)
Corn				
	(West and Marland, 2002)	1.3	131	Adding values in Table 7 NT or for CT and RT (21.78+6.7 l/ha) and (1.2+.35 GJ/ha) and (98+64 kg CO2/ha)
	(Adler et al., 2007)	**1.8**	**143**	No-till Table 1
	(Pimentel and Patzek, 2005)	5.9		Table 1 diesel + gasoline (4184 J/kcal)
	(Kim et al., 2009)	2.6		Avg of 8 locations in midwest from table 1 (excluded LPG)
Soybean				
	(West and Marland, 2002)	0.83	85.5	Adding values in Table 7 NT or for CT and RT (21.78+6.7 l/ha) and (1.2+.35 GJ/ha) and (98+64 kg CO2/ha)
	(Adler et al., 2007)	**1.8**	**124**	No-till Table 1
Cotton				
	(Chen and Baillie, 2009)	8 avg (**3.7** to 15.2)	800 (**275** to 1404)	in Australia from 7 farms in audit
Wheat				
	(West and Marland, 2002)	**0.83**	**85.5**	Adding values in Table 7 NT or for CT and RT (21.78+6.7 l/ha) and (1.2+.35 GJ/ha) and (98+64 kg CO2/ha)
Grassland		**0**	**0**	assumed no farm input

Bold values indicate those used for calculating differences for converting crops to switchgrass

Table B.5 Summary of LUC Impacts for Different Crops Based on Tables B1 – B4

Crop	GHG Soil ($kgCO^2\ ha^{-1}yr^{-1}$)	Fertilizer ($kgCO^2\ ha^{-1}yr^{-1}$)	Fertilizer ($GJ\ ha^{-1}yr^{-1}$)	Farm Machinery ($kgCO^2\ ha^{-1}yr^{-1}$)	Farm Machinery ($GJ\ ha^{-1}yr^{-1}$)	Nitrate Loss ($kgN\ ha^{-1}yr^{-1}$)
Grasslands	-750	257	5.1	114	1.5	-5.2
Hay	-920	-315	-6.3	59	0.8	-6.2
Corn	-3130*	-172	-3.4	-29	-0.3	-33.9
Soybean	-3130*	257	5.1	-10	-0.3	-14.6
Cotton	-3130*	0	0.0	-161	-2.2	-13.2
Wheat	-3130*	0	0.0	-10	-0.3	-20.6

A final summary of these estimates are provided in the document and used to as point estimates for overall LUC effects.

* GHG flux due to switchgrass conversion is assumed to be the same due to crop rotation and lack of consistent analysis from Table B2.

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